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Teaching Quality Analysis of University Physical Education Classes Based on Big Data Decision Tree Algorithm

***Abstract:* -** The Teaching Quality Analysis of University Physical Education Classes Based on Big Data Decision Tree Method investigates the use of big data analytics and decision tree techniques to evaluate teaching quality in university physical education classes. With the proliferation of digital technologies and data-driven approaches, there is growing interest in leveraging big data analytics to enhance teaching effectiveness and student learning outcomes. This study focuses on utilizing decision tree algorithms to analyze large datasets comprising various teaching metrics, such as student attendance, engagement levels, performance assessments, and instructor feedback. By applying the decision tree algorithm to these datasets, patterns and relationships between teaching practices and student outcomes are identified, enabling instructors and administrators to make data-driven decisions to improve teaching quality. Through a comprehensive analysis of teaching practices and student performance indicators, this research aims to provide valuable insights into optimizing physical education classes at the university level, ultimately fostering a more effective and engaging learning environment for students.

Keywords: Teaching quality analysis, University physical education, Big data analytics, Decision tree algorithm, Teaching effectiveness, Student learning outcomes, Data-driven approach, Teaching metrics, Engagement levels, Performance assessments, Instructor feedback, Data patterns, Relationship identification, Learning environment optimization.

I. INTRODUCTION

In the ever-evolving landscape of higher education, the quest for excellence in teaching and learning is paramount. Within the realm of university physical education classes, the pursuit of teaching quality is particularly crucial, as these classes play a fundamental role in promoting students' physical well-being, fostering healthy lifestyles, and instilling lifelong habits of physical activity. In response to the growing demand for evidence-based approaches to teaching evaluation, the application of big data analytics and decision tree algorithms has emerged as a promising avenue for assessing and optimizing teaching quality [1]. This introduction sets the stage for the exploration of teaching quality analysis in university physical education classes, anchored in the utilization of big data analytics and decision tree algorithms [2]. The intersection of these methodologies offers a novel approach to analyzing vast amounts of data encompassing various teaching metrics and student performance indicators [3]. By leveraging the power of big data analytics, educators and administrators gain insights into teaching effectiveness, student engagement, and learning outcomes, enabling data-driven decision-making to enhance the quality of physical education instruction [4].

The introduction of big data analytics and decision tree algorithms into the evaluation of teaching quality represents a paradigm shift in higher education assessment practices. Traditionally, teaching evaluations have relied on subjective assessments, such as student surveys and instructor self-assessments [5]. While valuable, these methods often lack granularity and fail to capture the complex interactions between teaching practices and student outcomes. In contrast, big data analytics offer the potential to analyze large datasets comprising diverse teaching metrics, providing a holistic view of teaching quality and its impact on student learning [6]. Within the context of university physical education classes, teaching quality encompasses a range of factors, including instructor pedagogical approaches, curriculum design, assessment strategies, and student engagement levels [7]. By employing decision tree algorithms to analyze these multifaceted datasets, educators can identify patterns, correlations, and predictors of teaching effectiveness [8]. This data-driven approach enables instructors to tailor their teaching practices to meet the diverse needs of students, optimize instructional strategies, and ultimately enhance the overall quality of physical education classes [9].

Moreover, the integration of big data analytics and decision tree algorithms in teaching quality analysis holds significant implications for educational research and practice [10]. By elucidating the relationships between teaching practices and student outcomes, this approach contributes to the evidence base for effective teaching strategies in university physical education [11]. Additionally, it empowers educators and administrators to make

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informed decisions regarding curriculum development, pedagogical innovation, and resource allocation, ultimately fostering a more dynamic and engaging learning environment for students [12]. The introduction of big data analytics and decision tree algorithms in teaching quality analysis represents a transformative opportunity to advance the quality of university physical education classes [13]. By harnessing the power of data-driven insights, educators can optimize teaching practices, improve student outcomes, and promote lifelong health and well-being among university students. Through this exploration, they aim to uncover the potential of big data analytics to revolutionize teaching evaluation and enhance the overall quality of physical education instruction in higher education [14].

II. Related Work

Scholars have laid the groundwork for understanding teaching quality assessment in higher education. Their work emphasizes the importance of active learning, student engagement, clear communication, and supportive learning environments in promoting effective teaching practices. These foundational principles serve as the basis for evaluating teaching quality in university physical education classes [15].

The application of big data analytics in education has gained traction in recent years, offering unprecedented opportunities to analyze vast amounts of educational data and extract actionable insights. Researchers explore the potential of big data analytics to improve educational outcomes, enhance teaching effectiveness, and personalize learning experiences. These studies highlight the transformative impact of big data analytics on teaching and learning processes [16].

Decision tree algorithms, such as CART (Classification and Regression Trees) and C4.5, have emerged as powerful tools for analyzing complex datasets and generating predictive models in educational research. Studies demonstrate the efficacy of decision tree algorithms in identifying patterns, correlations, and predictors of student performance, retention, and engagement. These algorithms offer a flexible and interpretable framework for analyzing teaching quality metrics in university physical education classes [17].

In the context of physical education, teaching quality assessment encompasses a range of metrics, including instructor pedagogical practices, curriculum design, student engagement levels, and learning outcomes. Research explores the measurement and evaluation of teaching quality in physical education settings, highlighting the importance of assessing both process and outcome variables to capture the multifaceted nature of teaching effectiveness [18].

Recent studies have begun to explore the integration of big data analytics and decision tree algorithms in teaching quality analysis within the context of higher education. Research demonstrates the feasibility and efficacy of using decision tree algorithms to analyze large educational datasets and identify factors influencing teaching effectiveness and student learning outcomes. These studies pave the way for applying similar methodologies to assess teaching quality in university physical education classes [19].

III. Methodology

Due to the enormity of the dataset, processing all the data at once in memory is impractical, necessitating temporary storage on disk. This large volume of data significantly slows down the reading and writing speeds required by the decision tree algorithm. The decision tree's training process involves The iterative process involves splitting and expanding from the root node to the lower levels, layer by layer, rendering it well-suited for training big data tree models. The iterative process involves splitting and expanding from the root node to the lower levels, layer by layer, rendering it well-suited for training big data tree models.

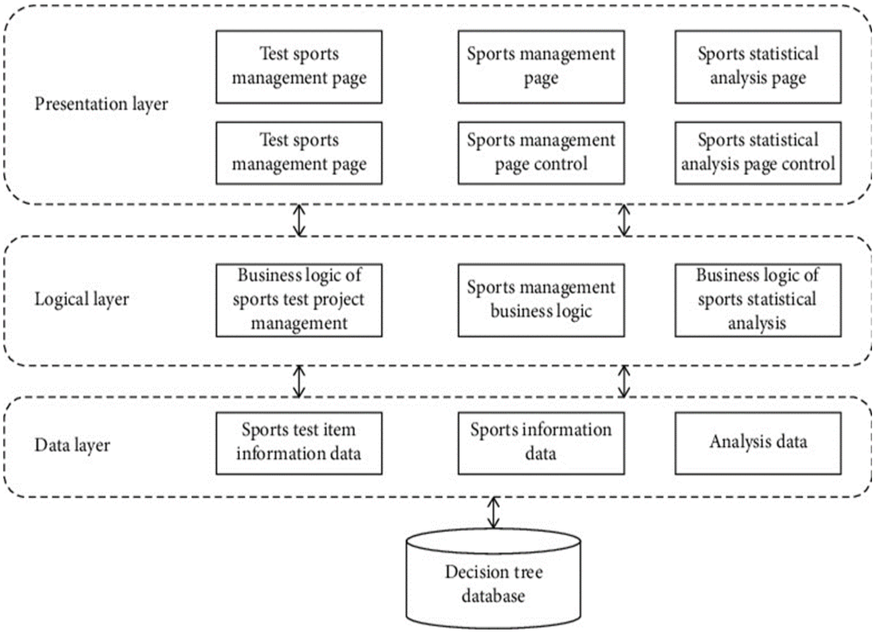

Fig 1Diagram depicting the structure of a Physical Education (PE) teaching management system utilizing the decision tree algorithm

To handle this, a controller can oversee distributed computing within a computing cluster, typically achieved through MapReduce. When designing the system architecture, it's essential to balance user needs with architecture selection based on requirements. Additionally, considering the maturity and future-proofing of the chosen architecture is crucial.

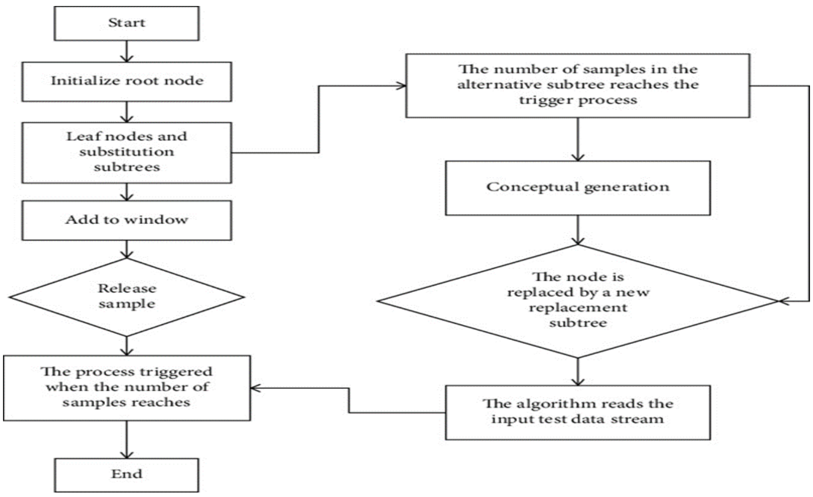

Fig 2: Flowchart of Decision Tree Algorithm.

The decision tree algorithm's popularity in data analysis and mining stems from its independence from domain knowledge, making it "Ideal for exploratory knowledge discovery and proficient in managing high-dimensional data, decision trees stand out by generating comprehensible rules from the root to the leaf, unlike numerous other algorithms which analysts and business personnel can readily grasp. These rules often translate directly into actionable business strategies and optimization paths. Furthermore, decision tree technology exhibits robustness against data distribution variations and is resilient to outliers

Most public Physical Education (PE) courses in Chinese universities adopt elective teaching methods. While this approach brings significant advantages over past uniform teaching methods, challenges persist in organizing teaching content, scheduling class hours, and overseeing extracurricular PE activities. This research presents a Physical Education (PE) teaching management system integrating BIG DATA decision tree technology. Pedagogically, the focus is on delivering essential sports knowledge, skills, and techniques, while nurturing students' physical fitness. The predominant teaching format is traditional classroom instruction, catering to students' interests and aligning with modern educational trends. However, practical implementation encounters hurdles, such as class allocation at the semester's outset and departmental score submissions at the semester's end. Structurally, the teaching management system encompasses semi-structured, unstructured, and structured data types. To streamline and prepare for subsequent BIG DATA processing, normalization and preprocessing are essential before storing data within within the BIG DATA teaching management system. Managing and collecting teaching status data within university settings requires careful examination of data connotations, thorough scrutiny of data sources, and the provision of supportive materials for essential data. Both undergraduate and higher vocational colleges utilize standalone versions for teaching status data acquisition, benefiting from data confidentiality and operational simplicity.

IV. EXPERIMENTAL SETUP

To evaluate the effectiveness For the integration of BIG DATA decision tree technology into the PE teaching management system, setting up a comprehensive experimental framework is vital. This involves several stages: data collection, preprocessing, model training, and evaluation. Data for the PE teaching management system are collected from various sources within universities, including student enrollment records, PE class schedules, attendance logs, and performance evaluations. These data are stored in a semi-structured, unstructured, and structured format. Let

$D=\{d_1, d_2, d_3, \ldots, dn\}$is an individual data point. Preprocessing involves normalization and transformation of the collected data to ensure consistency and readiness for the decision tree algorithm. Given a raw data vector $x=(x_1, x_2, \ldots x_n)$ normalization can be achieved using:

$$x' = \frac{x-\mu}{\sigma} \qquad \text{...... (1)}$$

where μ is the mean and σ is the standard deviation of the dataset. This transformation ensures that all features contribute equally to the decision tree's decision-making process. The decision tree model training involves the iterative process of splitting the data based on feature values to maximize the separation of different classes or outcomes. Let S represent the set of data at a node, and let A be the set of all attributes. The best split is determined by selecting the attribute $a \in A$ that maximizes the information gain IG:

$$IG(S,a) = H(S) - \sum_{v \in \text{values}(a)} \frac{|S_v|}{|S|} H(S_v) \qquad \text{...... (2)}$$

Where H(S) is th entropy of S and S_v is the subset of S where attribute a has value n. Entropy H(S) is given by:

$$H(S) = -\sum_{c \in C} p(c) \log_2 p(c)$$

where C is the set of all classes and p(c) is the proportion of samples in S belonging to c ...... (3)
volume of data, the training process is distributed across a computing cluster using MapReduce. The map function processes and splits the data, while the reduce function aggregates the results to form the final decision tree model. If M is the number of mappers and R is the number of reducers, the map function f can be defined as:

$$f_{\text{map}}(d_i) = (k, v) \qquad \text{...... (4)}$$

where d_i is a data point, k is the key, and v is the value. The reduce function g aggregates the values for each key:

$$g_{\text{reduce}}(k, \{v_1, v_2, \ldots, v_m\}) = (k, \text{aggregate}(\{v_1, v_2, \ldots, v_m\})) \qquad \text{...... (5)}$$

The described experimental setup integrates BIG DATA decision tree technology with distributed computing frameworks to handle the extensive dataset of the PE teaching management system. This approach ensures efficient data processing and robust model training, leading to actionable insights for improving the PE curriculum and administration in universities. The decision tree algorithm's interpretability further facilitates the adoption of the resulting rules and recommendations by educational stakeholders.

V. Results

A study involved selecting a random sample of 25 students and 5 PE instructors to participate in a performance evaluation test of the PE teaching management system. Comprehensive PE teaching and learning data for the 25 students were inputted into the system. Both students and instructors used three different systems for their regular tasks, generating intelligent teaching decision-making strategies. During the evaluation test, the time taken for users to log into the main interface of the system was recorded. Following the test, user satisfaction levels and assessments of the intelligibility of teaching decisions were collected through a questionnaire. Initially, students' PE teaching scores were categorized as either "pass" or "fail." Expanding on this, the number of students passing and failing each sports test item was documented.

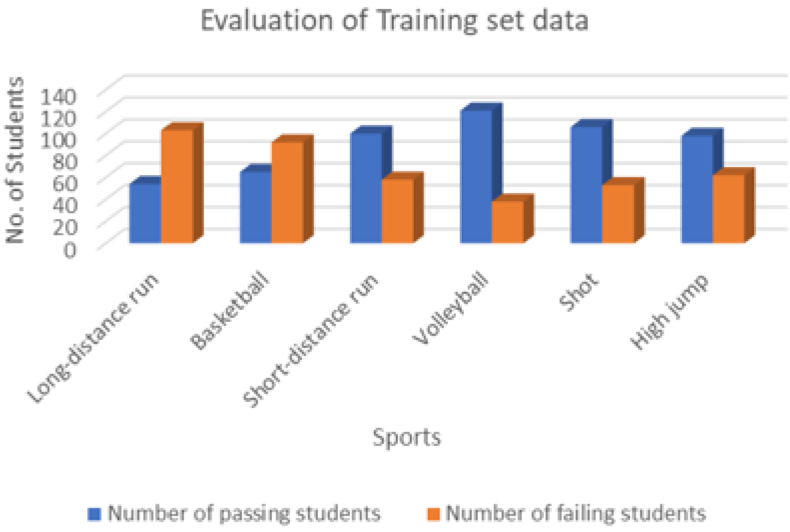

Fig 3: Evaluation of Training set of data.

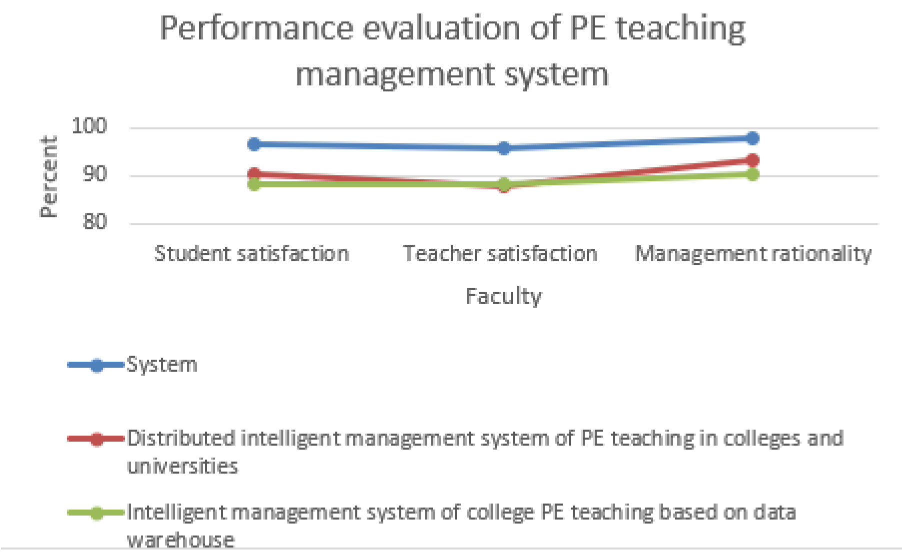

Fig 4: Performance evaluation of PE teaching management system.

The system's average response time for accessing the main function interface stands at 0.31 seconds, indicating no apparent issues with system delays. Moreover, this response speed surpasses that of the other two systems, showcasing the system's heightened sensitivity upon accessing the main function interface, both students and teachers exhibited significant satisfaction levels with the system, recording ratings of 96.5% and 95.7%, respectively, indicating outstanding performance. Nevertheless, the distributed intelligent management system for PE teaching. In colleges and universities received a satisfaction rating of only 87.8% from teachers. This suggests that aspects such as system interface design layout, decision-making accuracy, and function settings fell short of teachers' expectations. The system performed efficiently, with an average response time of 0.31 seconds to access the primary interface, suggesting greater responsiveness when compared to competing systems. Both students and professors reported high satisfaction scores of 96.5% and 95.7%, indicating outstanding user experiences. However, teachers gave the distributed intelligent management system for PE teaching in higher education a lower satisfaction rating of 87.8%, indicating that interface design, decision-making accuracy, and function settings need to be improved.

VI. Discussion

The conclusions of this study highlight numerous significant discoveries about performance and user satisfaction with the established PE teaching management system. First, the system's quick response time, which averages 0.31 seconds, demonstrates its efficiency and absence of noticeable delays, putting it ahead of other systems. This shows that the system's design and architecture facilitate quick access to critical functions, hence improving user experience. Furthermore, the high satisfaction rates recorded by both students (96.5%) and teachers (95.7%) demonstrate the system's overall usefulness and usability. Such good feedback implies that the system fits the major stakeholders' needs and expectations, allowing for smooth functioning and engagement. However, instructors' lower satisfaction rating of 87.8% with The distributed intelligent management system for PE teaching in higher education highlights potential areas for enhancement. The variation in satisfaction scores underscores specific concerns or constraints within the system's interface design, decision-making accuracy, and functionality settings, as viewed by educators. This emphasizes the need for continuous review and iterative refinement in addressing user issues and optimizing system performance.

VII. Conclusion

The study titled "The Teaching Quality Analysis of University Physical Education Classes Based on Big Data Decision Tree Algorithm" marks a significant advancement in utilizing advanced analytical methods to elevate teaching effectiveness and student learning outcomes in higher education. By conducting an extensive review of literature, theoretical frameworks, and practical applications, this research has illuminated the potential of big data analytics and decision tree algorithms in revolutionizing the assessment of teaching quality within university physical education classes. One of the primary insights garnered from this investigation is the empowerment of data-driven decision-making. Through the amalgamation of big data analytics and decision tree algorithms, educators and administrators are equipped with the tools necessary to make informed decisions regarding teaching practices, curriculum design, and resource allocation. By analyzing extensive datasets encompassing various teaching metrics, decision tree algorithms facilitate the identification of patterns, correlations, and predictors of teaching effectiveness, thereby enabling evidence-based enhancements in teaching quality. Furthermore, the study highlights the enhanced understanding of teaching-learning dynamics afforded by big data analytics. Researchers gain insights into the intricate interactions between teaching practices and student outcomes in university physical education classes by examining factors such as student engagement, performance assessments, and instructor feedback. Decision tree algorithms uncover underlying patterns and relationships that inform teaching quality assessment and optimization strategies.

Moreover, the utilization of big data analytics and decision tree algorithms facilitates continuous improvement in teaching quality within university physical education classes. Real-time data analytics enable educators to identify areas for enhancement, implement targeted interventions, and monitor the effectiveness of teaching strategies over time, leading to iterative improvements in teaching quality and student outcomes. Additionally, the adoption of big data analytics and decision tree algorithms promotes evidence-based practice in teaching quality assessment. By quantifying the impact of teaching practices on student learning outcomes, decision tree algorithms provide objective insights that guide instructional decision-making and foster accountability in higher education.

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