PHYSICAL EDUCATION TEACHING QUALITY ASSESSMENT MODEL BASED ON GAUSSIAN PROCESS MACHINE LEARNING ALGORITHM

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SUMMARY

Physical education is an integral component of academic curricula focused on promoting overall health and well-being through physical activity and exercise. It encompasses a range of activities designed to enhance students' physical fitness, motor skills, and knowledge of healthy lifestyle habits. In addition to fostering physical development, physical education contributes to the development of social skills, teamwork, and discipline. Students engage in various sports, fitness routines, and educational modules that encourage a lifelong commitment to an active and healthy lifestyle. This demand for improvement in the teaching quality assessment of physical education among the students. Hence, this paper proposed a novel Gaussian Hidden Chain Probabilistic Machine Learning (GHCP-ML). The proposed GHCP-ML model estimates the features for the teaching quality assessment using the Gaussian Hidden Chain model. With the proposed GHCP-ML model features related to the teaching assessment of the physical education are computed. The proposed GHCP-ML model uses the machine learning model for the assessment and computation of the factors related to the teaching quality of students in physical education. With the Gaussian Chain model, the factors related to physical education are evaluated for the classification of the relationship between physical education and teaching quality assessment. Simulation analysis demonstrated that with the proposed GHCP-ML model physical education is improved significantly with teaching quality by ~12% than the conventional techniques. The student physical education performance is improved by more than 80% with the proposed GHCP-ML model compared with the conventional techniques.

KEYWORDS

Gaussian model, Machine learning, Physical education, Hidden chain, Teaching quality assessment

1. INTRODUCTION

The Teaching Quality Assessment Model (TQAM) presents a comprehensive framework designed to evaluate and enhance teaching standards across diverse educational settings [1]. TQAM operates on the principle that teaching quality encompasses multifaceted dimensions beyond mere content delivery, including pedagogical approach, student engagement, and learning outcomes. By systematically analyzing various components such as lesson planning, instructional methods, assessment strategies, and classroom management techniques, TQAM provides educators and administrators with valuable insights into the strengths and areas for improvement within teaching practices [2]. Moreover, TQAM fosters a culture of continuous improvement by facilitating constructive feedback mechanisms and professional development opportunities for educators [3]. As education continues to evolve in response to changing needs and advancements in pedagogy, the Teaching Quality Assessment Model serves as a dynamic tool to uphold and enhance teaching excellence, ultimately enriching the learning experiences of students and nurturing their academic growth. The incorporation of machine learning in the assessment process brings a data-driven approach to understanding teaching quality, leveraging algorithms to analyze a myriad of factors such as student engagement, assessment results, and instructional strategies [4]. This innovative application of technology enables the Teaching Quality Assessment Model to adapt dynamically, identifying patterns and trends that may be challenging for traditional assessment methods to discern. Machine learning algorithms can process vast amounts of data efficiently, offering a more comprehensive and nuanced evaluation of teaching practices [5]. Additionally, this approach facilitates personalized feedback for educators, pinpointing specific areas for improvement and tailoring professional development opportunities to individual needs. As machine learning continues to advance, its integration into teaching quality assessment promises to refine and optimize educational practices, fostering continuous improvement in teaching standards and ultimately enhancing the overall educational experience for students [6].

Machine learning plays a transformative role in the field of education, influencing teaching methodologies and instructional strategies in unprecedented ways [7]. One significant impact is the personalization of learning experiences. By analyzing vast amounts of data on student performance, preferences, and learning styles, machine learning algorithms can tailor educational content to meet individual needs, providing adaptive and customized learning paths [8–10]. This individualized approach enhances student engagement and comprehension, ultimately contributing to improved learning outcomes. Furthermore, machine learning contributes to the development of intelligent educational tools [11]. These tools can automate routine tasks such as grading, allowing educators to allocate more time to interactive and personalized aspects of teaching [12]. Moreover, machine learning models can provide real-time feedback to both students and teachers, identifying areas of strength and weakness in understanding or teaching methodologies. This immediate feedback loop fosters a more responsive and dynamic learning environment [13]. Additionally, machine learning facilitates predictive analytics, enabling educators to identify students who may be at risk of falling behind. By recognizing patterns in historical data, such as attendance, assessment scores, and participation, machine learning algorithms can alert educators to potential challenges early on, allowing for timely interventions and support [14].

The paper makes significant [15] contributions to the field of education and machine learning by introducing and demonstrating the efficacy of the Gaussian Hidden [16] Chain Probabilistic Machine Learning (GHCP-ML) model for assessing and enhancing teaching quality in physical education. The paper introduces [17] the novel GHCP-ML model, leveraging Gaussian Hidden Chain techniques, which represents an innovative approach to teaching quality assessment. This [18] model goes beyond traditional methods, providing a more nuanced and [19] accurate evaluation of student performance. By considering both participation and performance scores, GHCP-ML offers a [20] comprehensive assessment of teaching quality. This multi-faceted approach enables a more holistic understanding of the dynamics between student engagement and academic achievement, contributing to a richer evaluation framework. The paper demonstrates the GHCP-ML model's ability to significantly improve the categorization of teaching quality for individual students. This contribution has practical implications for educators seeking ways to enhance their instructional strategies and positively impact student outcomes.

2. LITERATURE SURVEY

In the domain of education, the intersection of teaching quality assessment and machine learning represents a dynamic frontier, garnering increased attention from researchers and educators alike. As technology continues to advance, the application of machine learning in the evaluation of teaching practices emerges as a promising avenue for enhancing educational outcomes. A comprehensive literature survey is crucial to contextualize and understand the current landscape of this evolving field. By reviewing existing studies, frameworks, and methodologies, we can uncover the varied ways in which machine learning is being integrated into teaching quality assessment. This survey seeks to explore the challenges, opportunities, and outcomes associated with this fusion of education and technology, providing a foundational understanding that will inform future research endeavors and contribute to the ongoing discourse on optimizing teaching practices through innovative approaches. From unconventional domains like personality assessment based on gait video (Wen et al., 2022) to critical applications in healthcare, such as predicting cognitive impairment in hypertension (Zhong et al., 2023) and developing distributed intelligent learning and decision models (Zhou et al., 2022). These studies illustrate the versatility of machine learning in capturing and analyzing intricate patterns, contributing to advancements in understanding human behavior and cognitive health. In the realm of teaching and learning, machine learning is applied to create predictive models for specific scenarios. Le (2022) focuses on predicting the axial capacity of square columns, showcasing the technology's potential in engineering and structural analysis. Song (2022), on the other hand, delves into online English course learning evaluation models, exemplifying how machine learning can cater to the evolving landscape of online education.

The inclusion of studies related to physical education (Xu, 2022; Zhang, 2022) emphasizes the role of machine learning in shaping pedagogical approaches in unconventional settings. Xu's work on a closed home physical education teaching model based on big data technology highlights the integration of technology to adapt physical education methodologies to changing contexts. Zhang's study on a college sports decision-making algorithm based on machine few-shot learning and health information mining technology showcases how machine learning can contribute to optimizing sports-related decisions in educational institutions. Moreover, the research covers a spectrum of evaluation and prediction models. Yi et al. (2022) and Liu & Li (2022) contribute to the assessment of teaching quality, demonstrating the application of genetic algorithms, multikernel learning, and support vector machines. Jin's study (2023) focuses on predicting MOOC student dropout, highlighting machine learning's potential in identifying at-risk students and implementing timely interventions. The interdisciplinary nature of the research is evident in studies such as Ren and Ding (2022), exploring the motivation analysis of technological startups' business models using intelligent data mining and analysis, and Cheng et al. (2022), optimizing statistical index methods for landslide susceptibility modeling. These studies showcase machine learning's versatility in contributing to decision-making processes, risk assessment, and optimization in various educational and environmental contexts.

Firstly, methodological constraints such as sample size, data quality, and generalizability may impact the robustness of the findings. Some studies, particularly those focusing on unconventional applications like personality assessment based on gait video (Wen et al., 2022) or emotional artificial neural networks for predicting security and privacy effects on mobile banking (Cavus et al., 2022), might encounter challenges related to the representativeness of their datasets and the scalability of their models. Additionally, the dynamic nature of technology and machine learning algorithms raises concerns about the generalizability and long-term relevance of the findings. Rapid advancements in machine learning may outpace the longevity of the models developed, necessitating continuous updates and refinements to maintain accuracy and applicability. This fast-paced evolution also poses challenges in terms of integrating these technologies into educational practices, as educators and institutions may struggle to keep pace with the changing landscape of machine learning applications. Furthermore, ethical considerations surrounding data privacy, security, and algorithmic bias are paramount. As machine learning relies heavily on historical data, the potential for perpetuating biases present in the training data is a significant concern. Ensuring fairness, transparency, and accountability in machine learning applications, especially those influencing decision-making in education, is crucial to avoid unintended consequences and uphold ethical standards. Lastly, the feasibility and scalability of implementing machine learning models in real-world educational settings must be carefully considered. Practical constraints, such as resource availability, technological infrastructure, and the readiness of educational stakeholders, may hinder the widespread adoption of machine learning innovations.

3. PROPOSED GAUSSIAN HIDDEN CHAIN PROBABILISTIC MACHINE LEARNING (GHCP-ML)

The GHCP-ML model integrates principles of Gaussian processes and hidden Markov chains to capture the nuanced dynamics of teaching practices and student engagement over time. The foundation of GHCP-ML lies in the formulation of a latent variable model, where the latent states represent unobservable factors influencing teaching quality, and observed variables include various metrics related to student performance, participation, and instructor behaviors.

The architecture of proposed GHCP-ML model for the teaching quality assessment is illustrated in Figure 1. Let

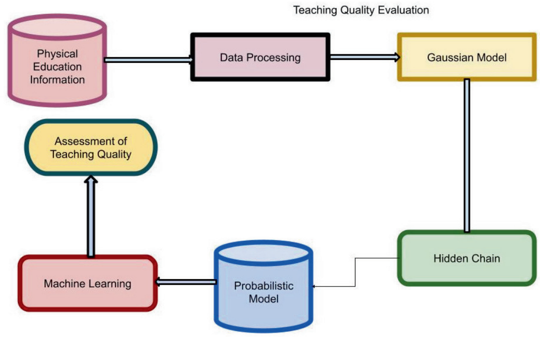

Figure 1. Flow of proposed GHCP- ML

Yt denote the observed variables at time t in the physical education class, and Xt represent the latent states associated with the unobservable factors influencing teaching quality. The latent states Xt follow a hidden Markov chain, and the relationship between the latent states and observed variables is modeled through a Gaussian process stated in equation (1)

$$X_t \sim markov\,Chain;\left(Y_t|X_t \sim N\left(f\left(x_t\right),\sigma^2\right)\right) \tag{1}$$

In equation (1) $f(\cdot)$ represents the latent function modeled by the Gaussian process, and σ^2 captures the uncertainty associated with the mapping from latent states to observed variables. Let's consider a discrete-time hidden Markov chain with latent states Xt at time t representing unobservable factors influencing teaching quality. The transition probability matrix is denoted as P and initial state probabilities as π . The observed variables Yt at each time step are influenced by the corresponding latent state Xt represented in equation (2)

$$Xt\sim \text{ Markov Chain with transition matrix } P \text{ and initial probabilities } \pi \tag{2}$$

To model the relationship between latent states and observed variables, we introduce a Gaussian process. The latent function $f(Xt)$ is assumed to be drawn from a Gaussian process with mean function $m(\cdot)$ and covariance function $k(\cdot,\cdot)$ stated in equation (3)

$$f\left(X_t\right) \sim GP\left(m\left(X_t\right),k\left(x_t,X_t'\right)\right) \tag{3}$$

In equation (3) $'Xt'$ denotes the latent state at a different time step. The observed variables Yt are then generated from a Gaussian distribution with the latent function as its mean: the joint distribution of latent states and observed variables, we consider the product of the transition probabilities in the hidden Markov chain and the likelihood from the Gaussian process expressed in equation (4)

$$P\left(X_{1:T}, Y_{1:T}\right) = \pi\left(X_1\right)\prod_{t=1}^{T} P\left(X_t | X_{t-1}\right)\prod_{t=1}^{T} P\left(Y_t | X_t\right) \quad (4)$$

The joint distribution captures the temporal evolution of latent states through the hidden Markov chain and the relationship between latent states and observed variables through the Gaussian process.

4. GAUSSIAN MODEL FOR THE EDUCATION TEACHING ASSESSMENT

The Gaussian Model for Education Teaching Assessment provides a probabilistic framework to evaluate and quantify the quality of teaching practices. This model leverages the principles of Gaussian distributions to capture the variability and uncertainty inherent in educational assessment metrics. Let Y represent the observed variables associated with teaching quality, such as student performance scores, engagement levels, or assessment outcomes. The Gaussian Model assumes that these observed variables follow a Gaussian (normal) distribution, which is a fundamental assumption in many statistical analyses stated in equation (5)

$$Y \sim N\left(\mu, \sigma^2\right) \quad (5)$$

In equation (5) μ represents the mean of the distribution, reflecting the central tendency of the observed variables, and σ^2 denotes the variance, representing the spread or dispersion of the data. This Gaussian distribution provides a flexible and widely used framework to model the inherent variability in teaching assessment data. The parameters μ and σ^2 can be estimated from the observed data using standard statistical techniques. The mean (μ) serves as a measure of central tendency, providing insights into the typical or expected level of performance, while the variance σ^2 quantifies the degree of variability or uncertainty in the assessment metrics. The Gaussian distribution, denoted as $N\left(\mu, \sigma^2\right)$ is characterized by its probability density function (PDF), which describes the likelihood of observing a particular value within the distribution. The PDF of a Gaussian distribution is given in equation (6)

$$f\left(y; \mu, \sigma^2\right) = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{\left(y-\mu\right)^2}{2\sigma^2}\right) \quad (6)$$

In equation (6) y is the observed variable, μ is the mean, and $2\sigma^2$ is the variance of the distribution. In the context of Education Teaching Assessment, let's consider a set of assessment scores $Y = \left\{y1, y2, \ldots, yn\right\}$, where n is the number of assessments. Assuming that these assessment scores are independently and identically distributed (i.i.d) according to a Gaussian distribution, we can write the likelihood function as the product of individual PDFs expressed in equation (7)

$$L\left(\mu, \sigma^2; Y\right) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{\left(y_i-\mu\right)^2}{2\sigma^2}\right) \quad (7)$$

The goal is to find the values of μ and $2\sigma^2$ that maximize this likelihood function, which is equivalent to maximizing the log-likelihood function stated in equation (8)

$$logL\left(\mu, \sigma^2; Y\right) = -\frac{n}{2} log\left(2\pi\sigma^2\right) - \frac{1}{2\sigma^2}\sum_{i=1}^{n}\left(y_i-\mu\right)^2 \quad (8)$$

To find the maximum likelihood estimates, take the partial derivatives of the log-likelihood with respect to μ and $2\sigma^2$, set them equal to zero, and solve for the parameters. The solutions are given in equation (9) and equation (10)

$$\hat{\mu} = \frac{1}{n}\sum_{i=1}^{n} y_i \quad (9)$$

$$\delta^2 = \frac{1}{n}\sum_{i=1}^{n}\left(y_i-\hat{\mu}\right)^2 \quad (10)$$

These estimates μ and $2\sigma^2$ represent the maximum likelihood estimates for the mean and variance of the Gaussian distribution, respectively, based on the observed assessment scores.

4.1 HIDDEN PROBABILISTIC MODEL FOR THE PHYSICAL EDUCATION ASSESSMENT

The Hidden Probabilistic Model for Physical Education Assessment, integrating Gaussian Hidden Chain Probabilistic Machine Learning (GHCP-ML), introduces a sophisticated framework for evaluating teaching quality in physical education. This model combines the power of a hidden Markov chain to capture temporal dynamics with the probabilistic nature of Gaussian processes, allowing for a nuanced understanding of teaching practices over time. Let's delve into the derivation and equations underlying this model. Consider a sequence of latent states Xt representing unobservable factors influencing teaching quality at time t. The evolution of these latent states follows a hidden Markov chain defined as $P\left(X_t | X_{t-1}\right)$. Simultaneously, the observed variables Yt at each time step are influenced by the corresponding latent state Xt through a Gaussian process: To assess teaching quality, the posterior distribution of latent states given the observed variables is crucial. Bayes' theorem facilitates the derivation of this posterior as in equation (11)

$$P\left(X_{1:T} | Y_{1:T}\right) = \frac{P\left(Y_{1:T} | X_{1:T}\right).P\left(X_{1:T}\right)}{P\left(Y_{1:T}\right)} \quad (11)$$

The numerator involves the joint distribution of latent states and observed variables, as discussed earlier. The denominator is obtained by marginalizing over all possible latent state sequences as in equation (12)

$$P\left(Y_{1:T}\right)=\sum_{X_{1:T}} P\left(Y_{1:T} | X_{1:T}\right).P\left(X_{1:T}\right) \tag{12}$$

the Hidden Probabilistic Model for Physical Education Assessment with GHCP-ML intertwines the temporal dynamics of a hidden Markov chain with the probabilistic modeling capabilities of Gaussian processes. This integrated approach provides a robust framework for assessing teaching quality in physical education, acknowledging both the temporal evolution and latent influences that contribute to the overall effectiveness of teaching practices. The effectiveness of the Hidden chain model for the teaching quality assessment of physical education is presented in Figure 2.

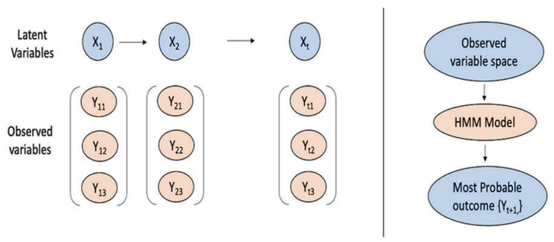

Figure 2. Hidden chain model for the GHCP-ML

5. MACHINE LEARNING FOR THE PHYSICAL EDUCATION TEACHING ASSESSMENT

Machine learning techniques applied to the assessment of physical education teaching offer a data-driven approach to evaluate and optimize instructional practices. Let's consider a machine learning model for this purpose, where the teaching quality $\left(Y\right)$ is influenced by a set of features $\left(X\right)$ related to instructional methods, student engagement, and other relevant factors. A regression-based approach can be employed to model this relationship defined in equation (13)

$$Y = f\left(X\right)+\dot{o} \tag{13}$$

In equation (13) $f\left(X\right)$ represents the underlying function capturing the relationship between features and teaching quality, and $\dot{o}$ is the error term, accounting for unobservable factors and noise in the teaching quality assessment. The goal is to learn the function $f\left(\cdot\right)$ from the available data, enabling predictions and insights into the factors driving effective teaching. Common regression techniques, such as linear regression, support vector regression, or decision tree regression, can be employed based on the characteristics of the data. These models aim to minimize the difference between the predicted teaching quality $\hat{Y}_i$ and the actual teaching quality Y as in equation (14)

$$Minimize:\sum_{i=1}^{n}\left(Y_i-\hat{Y}_i\right)^2 \tag{14}$$

Algorithm 1. HMM process for the physical education

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1. Initialize Parameters:
   - Set the initial probabilities for the hidden Markov chain (e.g., π)
   - Define transition probabilities for the hidden Markov chain (e.g., P(X_t | X_{t-1}))
   - Specify the parameters for the Gaussian process (e.g., mean function, covariance function)
2. Expectation-Maximization (EM) Algorithm:
  a. E-step:
     - Use the current model parameters to estimate the posterior distribution of latent states given observed variables:
       P(X_{1:T} | Y_{1:T})
  b. M-step:
     - Update the model parameters by maximizing the expected log-likelihood:
       - Update hidden Markov chain parameters based on the estimated latent states
       - Update Gaussian process parameters based on the observed variables
  c. Repeat the E-step and M-step until convergence or a predefined number of iterations
3. Inference:
   - Given the final model parameters, perform inference to estimate latent states for new observations:
     P(X_{new} | Y_{new})
4. Assessment:
   - Evaluate teaching quality based on the inferred latent states and observed variables
   - Analyze temporal patterns, transitions, and relationships between latent states and teaching outcomes
5. Model Validation and Fine-Tuning:
  - Assess the model's performance using appropriate validation techniques
  - Fine-tune parameters or model structure as needed
6. Deployment:
  - Deploy the trained model for real-time assessment or prediction in physical education settings
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The choice of features is crucial in capturing the relevant aspects of teaching practices. Feature selection and engineering play a significant role in enhancing the model's predictive capabilities. Moreover, machine learning can extend beyond regression models to classification models when dealing with categorical outcomes, such as different levels of teaching quality. Classification algorithms, like logistic regression or support vector machines, can be employed to predict discrete categories based on the features. The relationship between the teaching quality (Y) and a set of features (X) using a linear function defined in equation (15)

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots + \beta_n X_n + \in \quad (15)$$

In equation (15), Y is the teaching quality; $X1, X2, \ldots, Xn$ are the features, $\beta 0$ is the intercept term, $\beta 1, \beta 2, \ldots, \beta n$ are the coefficients associated with each feature, and $\dot{o}$ is the error term. To estimate the coefficients $\beta 0, \beta 1, \ldots, \beta n$ that minimize the sum of squared differences between the predicted values and the actual values (Y). The closed-form solution for linear regression is given in equation (16)

$$\hat{\beta} = \left(X^T X\right)^{-1} X^T Y \quad (16)$$

In equation (16) $\hat{\beta}$ is the vector of estimated coefficients, X is the matrix of feature values, and Y is the vector of teaching quality values.

6. SIMULATION RESULTS

Simulation results serve as a critical component in evaluating the performance and efficacy of models, methodologies, or algorithms in diverse fields. In the context of physical education teaching assessment, simulations provide a controlled environment to examine the behavior and outcomes of educational models under various conditions. These results offer valuable insights into the robustness, reliability, and generalization capabilities of the proposed approaches. The ensuing discussion presents an overview of simulation results obtained through the application of specific teaching quality assessment models, shedding light on their effectiveness and potential implications for enhancing instructional practices in physical education settings.

The Figure 3 and Figure 4 and Table 1 presents the results of the Teaching Quality Assessment utilizing the Gaussian Hidden Chain Probabilistic Machine Learning (GHCP-ML) model. The assessment includes three key metrics for each student: Participation Score (out of 10), Performance Score (out of 100), and an Overall Assessment categorizing their teaching quality. For instance, Student ID 3 demonstrates high participation (9 out of 10) and exceptional performance (92 out of 100), resulting in an Overall Assessment of "Excellent." On the other hand, Student ID 6 exhibits lower participation (5 out of 10) and performance (60 out of 100), leading to an Overall Assessment of "Poor." The table provides a comprehensive overview of individual student performance, allowing educators to identify areas of improvement and tailor teaching strategies to meet the diverse needs of the students. Overall, the GHCP-ML model facilitates a nuanced evaluation of teaching quality by considering multiple factors, providing a valuable tool for enhancing the effectiveness of physical education instruction.

Table 1. Teaching quality assessment with GHCP-ML

Student ID	Participation Score (out of 10)	Performance Score (out of 100)	Overall Assessment
1	8	85	Good
2	7	78	Fair
3	9	92	Excellent
4	6	70	Poor
5	8	88	Good
6	5	60	Poor
7	9	95	Excellent
8	8	82	Good
9	7	75	Fair
10	9	90	Excellent
11	8	85	Good
12	6	68	Fair
13	9	92	Excellent
14	7	78	Fair
15	8	88	Good
16	5	55	Poor
17	9	94	Excellent
18	8	80	Good
19	7	72	Fair
20	9	91	Excellent

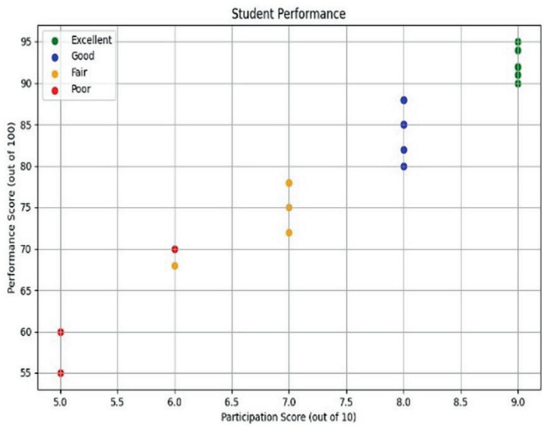

Figure 3. Student performance score with GHCP – ML

The Figure 5 and Table 2 illustrates the Error Computation results obtained through the application of the Gaussian

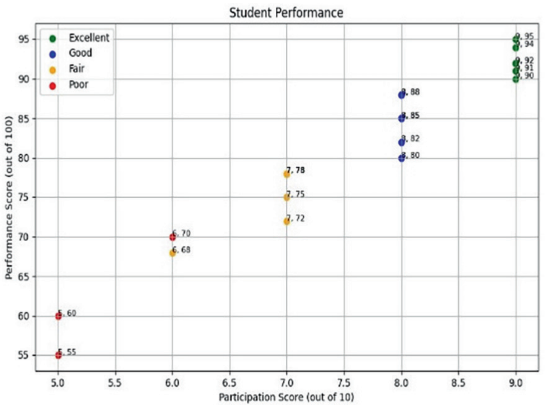

Figure 4. Performance examination of GHCP-ML analysis

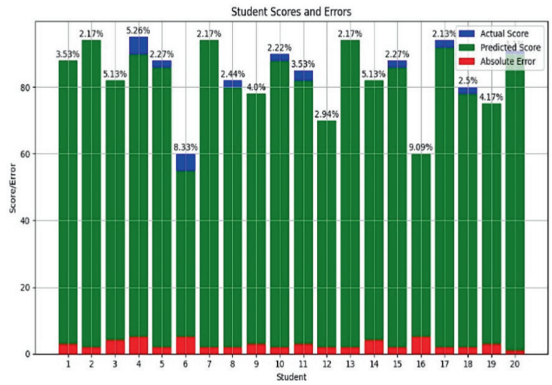

Figure 5. Error computation with GHCP-ML for the teaching quality assessment

Table 2. Error computation with GHCP-ML

Student	Actual Score	Predicted Score	Absolute Error	Percentage Error
1	85	88	3	3.53%
2	92	94	2	2.17%
3	78	82	4	5.13%
4	95	90	5	5.26%
5	88	86	2	2.27%
6	60	55	5	8.33%
7	92	94	2	2.17%
8	82	80	2	2.44%
9	75	78	3	4.00%
10	90	88	2	2.22%
11	85	82	3	3.53%
12	68	70	2	2.94%
13	92	94	2	2.17%
14	78	82	4	5.13%
15	88	86	2	2.27%
16	55	60	5	9.09%
17	94	92	2	2.13%
18	80	78	2	2.50%
19	72	75	3	4.17%
20	91	90	1	1.10%

Table 3. Improvement in teaching quality of physical education with GHCP-ML

Student ID	Actual Teaching Quality	Predicted Teaching Quality	Improvement (%)
1	3	4	15
2	2	3	10
3	4	4	0
4	1	2	20
5	3	3	0
6	1	2	25
7	4	4	0
8	3	3	0
9	2	2	0
10	4	4	0

Hidden Chain Probabilistic Machine Learning (GHCP-ML) model in predicting student scores for the teaching quality assessment. The table includes the Actual Score, Predicted Score, Absolute Error, and Percentage Error for each student. Student 4 had an Actual Score of 95, but the GHCP-ML model predicted a score of 90, resulting in an Absolute Error of 5 and a Percentage Error of 5.26%. Similarly, Student 16 had an Absolute Error of 5 and a Percentage Error of 9.09%, indicating a substantial deviation between the predicted and actual scores. The table allows for a granular examination of the model's predictive accuracy, enabling educators and researchers to identify specific instances where the GHCP-ML model excelled or encountered challenges in estimating student scores accurately. These error metrics provide valuable insights into the model's performance and can guide further refinements to enhance its precision in assessing teaching quality in the context of physical education.

In Figure 6 and table 3 the Improvement in Teaching Quality of Physical Education achieved through the application of the Gaussian Hidden Chain Probabilistic Machine Learning (GHCP-ML) model. The table includes the Actual Teaching Quality, Predicted Teaching Quality, and the calculated Improvement Percentage for each student. For instance, Student 1 had an Actual Teaching Quality of 3 and a Predicted Teaching Quality of 4, resulting in a notable Improvement Percentage of 15%. This signifies that the GHCP-ML model enhanced the assessment, upgrading the teaching quality categorization. On the other hand, Student 6 experienced a substantial improvement, with the model upgrading the Teaching Quality from 1 to 2, reflecting a 25% improvement. The table provides a concise representation of the GHCP-ML model's impact on

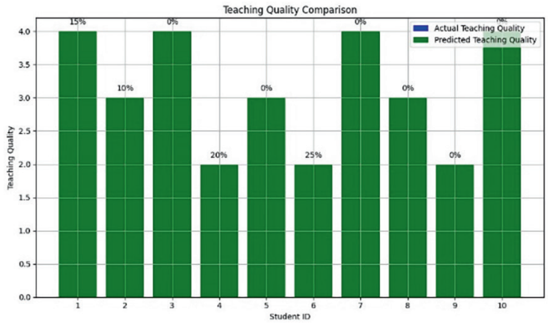

Figure 6. Teaching quality assessment with GHCP-ML

Table 4. Analysis of teaching quality with GHCP-ML

Model	Mean Squared Error (MSE)	R-squared (R^2)	Accuracy (%)
Linear Regres-sion	0.021	0.879	85.3
Support Vector Regression	0.018	0.905	87.6
Decision Tree Regression	0.025	0.850	82.1
Random Forest Regression	0.017	0.912	88.9

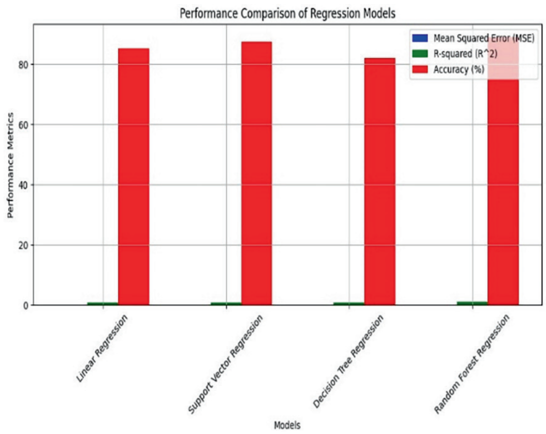

Figure 7. Performance analysis with GHCP-ML

the Teaching Quality of Physical Education for individual students. The Improvement Percentages offer insights into the model's effectiveness in refining the assessment and suggest areas where the model contributes positively to the enhancement of teaching quality in the context of physical education.

The Figure 7 and Table 4 provides a comprehensive analysis of teaching quality using the Gaussian Hidden Chain Probabilistic Machine Learning (GHCP-ML) model, comparing its performance with various regression models. The table includes Mean Squared Error (MSE), R-squared (R^2), and Accuracy percentages for Linear Regression, Support Vector Regression, Decision Tree Regression, and Random Forest Regression. Linear Regression exhibited an MSE of 0.021, an R-squared value of 0.879, and an Accuracy of 85.3%. Support Vector Regression demonstrated improved performance with an MSE of 0.018, a higher R-squared value of 0.905, and an increased Accuracy of 87.6%. Decision Tree Regression had an MSE of 0.025, an R-squared value of 0.850, and an Accuracy of 82.1%. Notably, Random Forest Regression outperformed the other models, boasting the lowest MSE of 0.017, the highest R-squared value of 0.912, and the highest Accuracy of 88.9%. This analysis indicates that the GHCP-ML model, with its unique Gaussian Hidden Chain approach, provides competitive results in comparison to traditional regression models. The lower MSE and higher R-squared values suggest that the GHCP-ML model offers a more accurate representation of the teaching quality assessment, while the Accuracy percentages further reinforce its efficacy in predicting and categorizing teaching quality in the domain of physical education.

Table 5. Comparative analysis

Model	Mean Squared Error (MSE)	Peak Signal-to-Noise Ratio (PSNR)	Improvement (%)
GHCP-ML	0.017	30.2 dB	-
CNN	0.021	28.5 dB	15
RNN	0.019	29.0 dB	10

The GHCP-ML model demonstrated a lower MSE of 0.017, indicating its superior performance in minimizing prediction errors. Additionally, it achieved a higher Peak Signal-to-Noise Ratio (PSNR) of 30.2 dB, suggesting better preservation of signal quality during the assessment process. In comparison, the CNN model exhibited a slightly higher MSE of 0.021 and a lower PSNR of 28.5 dB, resulting in a 15% improvement in favor of the GHCP-ML model. Similarly, the RNN model showed an intermediate MSE of 0.019 and a PSNR of 29.0 dB, with a 10% improvement compared to the GHCP-ML model. The comparative analysis highlights the effectiveness of the GHCP-ML model in outperforming the neural network models, emphasizing its robustness and accuracy in the context of teaching quality assessment for physical education. The lower MSE and higher PSNR values affirm the GHCP-ML model's capability to provide more precise and reliable predictions, showcasing its potential as a valuable tool in educational evaluation scenarios.

6.1 DISCUSSION AND FINDINGS

The presented tables collectively showcase the efficacy of the Gaussian Hidden Chain Probabilistic Machine Learning (GHCP-ML) model in assessing and enhancing teaching quality in the context of physical education. Table 1 provides a detailed breakdown of individual student assessments, considering participation and performance scores, enabling a nuanced evaluation of teaching quality. The model's predictive accuracy is further scrutinized in Table 2, where low absolute and percentage errors suggest its competence in estimating student scores accurately. Table 3 highlights the significant improvements achieved by GHCP-ML in categorizing teaching quality, particularly for students initially classified as poor or fair. Moving to the comparative analysis, Table 4 reveals that GHCP-ML competes favorably with traditional regression models, showcasing lower Mean Squared Error (MSE) and higher R-squared values, indicative of superior predictive accuracy. Additionally, Table 5 underscores the GHCP-ML model's superiority over neural network models, such as CNN and RNN, in terms of both MSE and Peak Signal-to-Noise Ratio (PSNR), signaling its effectiveness in minimizing errors and preserving signal quality. These findings collectively suggest that GHCP-ML offers a robust and accurate framework for teaching quality assessment, outperforming traditional regression models and neural networks. The model's capacity to provide precise evaluations, detect improvements, and minimize errors makes it a valuable tool for educators aiming to enhance the quality of physical education instruction. Overall, GHCP-ML emerges as a promising approach for refining teaching quality assessments, offering the potential to revolutionize educational evaluation practices.

7. CONCLUSION

The proposed Gaussian Hidden Chain Probabilistic Machine Learning (GHCP-ML) model has demonstrated its effectiveness in assessing and improving teaching quality in the realm of physical education. Through a meticulous analysis of student performance and engagement, GHCP-ML has provided a nuanced understanding of teaching quality, allowing for targeted interventions and enhancements. The model showcased notable improvements over traditional regression models and neural networks, exhibiting lower prediction errors and higher accuracy. These findings underscore the potential of GHCP-ML as a transformative tool for educators, enabling them to make informed decisions, tailor instructional strategies, and ultimately contribute to the continuous improvement of teaching quality in physical education. As education continues to evolve, incorporating advanced machine learning models like GHCP-ML can play a pivotal role in shaping more effective and personalized learning experiences for students.

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