Exploring Student Learning Interests with Support Vector Machine in Pedagogical Strategies

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Abstract—**In the realm of education and instructional design, understanding the impact of pedagogical strategies on students' learning interest is of paramount importance. This study employs a machine learning approach, specifically Support Vector Machines with a linear kernel, to comprehensively explore this relationship. The research investigates the influence of various pedagogical strategies on students' learning interest using classification techniques. Our findings reveal robust model capabilities, with an Area Under the Curve of 93.3%, Classification Accuracy of 95%, precision of 95.3%, and recall of 95%. Feature importance analysis identifies key contributors, with the 'Inclusive Learning Environment' and 'Active Class Discussions' aspects showing significant influence. Our research underscores the critical role of pedagogical strategies, particularly in shaping the learning environment and promoting active class discussions, as they significantly impact students' learning interest. This study enriches our understanding of the model's capabilities and highlights the need to consider real-world contexts and validate its performance on external datasets for successful application and generalization. As educators and institutions aim to create engaging and effective learning environments, the insights derived from this research offer actionable recommendations for improving pedagogical strategies. This research serves as a valuable resource for those seeking to enhance the learning experiences of students, providing a foundation for further exploration of pedagogical dynamics and their influence on student learning interest.**

***Keywords*—Pedagogical Strategies, Learning Interest, Classification, Support Vector Machines, Linear Kernel, Feature Importance**

I. Introduction

Pedagogical strategies encompass a diverse set of methods, techniques, and approaches employed by educators to facilitate teaching and enhance student learning [1]. These strategies are pivotal in achieving specific learning objectives and catering to the diverse needs of students [2]. In the realm of education and instructional design, understanding the impact of pedagogical strategies on students' learning interest is of paramount importance [3]. As educators and institutions strive to create engaging and effective learning environments, it becomes imperative to explore the intricate relationship between teaching techniques and students' enthusiasm for learning [4].

Recent years have witnessed a growing interest in examining the connection between pedagogical strategies and students' learning interest [5]–[8]. While these studies have contributed valuable insights, there exists a significant gap in the literature when it comes to comprehensively exploring the influence of various aspects of pedagogical strategies. In this context, our research embarks on a distinctive journey. We aim to investigate the influence of pedagogical strategies on students' learning interest while placing a specific focus on eight distinct dimensions of pedagogical strategies. These dimensions encompass teaching techniques, the integration of visual media, the utilization of technology, engagement in practical activities, the application of project-based teaching methods, the establishment of inclusive learning environments, the facilitation of active class discussions, and the allocation of interactive learning time. Our study aims to uncover how these diverse facets of pedagogical strategies impact students' learning interest by employing a classification approach using machine learning.

This research employs a comprehensive methodology that encompasses various stages. We meticulously detail our approach to data collection, including the questionnaire items employed to evaluate pedagogical strategies and learning interest. Furthermore, we subject our data to rigorous validity and reliability tests to ensure the credibility and stability of our dataset. Our research methodology integrates advanced machine learning techniques, with a specific focus on the application of Support Vector Machines (SVM) employing a linear kernel. To assess the performance of our classification model, we employ a robust 10-fold cross-validation approach, which is accompanied by performance metrics such as ROC-AUC, Classification Accuracy (CA), Precision, and Recall. Additionally, feature analysis plays a pivotal role in our research as we utilize the permutation feature importance (PFI) method to scrutinize the significance of individual features within our model.

In conclusion, our research stands as a significant contribution to both the fields of education and machine learning. We not only enhance the understanding of the intricate relationship between pedagogical strategies and student learning interest but also introduce a novel approach for dissecting the relative importance of these strategies. This study provides educators, institutions, and policymakers with actionable insights to foster more engaging and effective learning environments. Our research serves as a cornerstone for future investigations into the dynamics of pedagogical strategies and their profound impact on students' learning interest.

II. Research Methods

In the Research Method section, we employed a comprehensive set of methodologies to conduct our study. Our methodology can be divided into six core subsections, each playing a crucial role in the research process. Each of these subsections contributes to a comprehensive research methodology that underpins the integrity and rigor of our study.

A. Data Collection

In this research study, data were collected from a sample of 100 students enrolled at SMK Tunas Pelita Binjai. The data collection involved the administration of a 10-question questionnaire. These questionnaire items addressed eight key aspects related to pedagogical strategies, specifically focusing on teaching techniques [9], the utilization of visual media [10], the incorporation of technology [11], engagement in practical activities [12], the implementation of project-based teaching methods [13], the establishment of an inclusive learning environment [14], active class discussions [15], and the allocation of interactive learning time [16].

Additionally, to assess students' learning inclinations, two questionnaire items were designed to measure their interest in real-world applications and their inclination toward independent research and self-directed learning. This approach facilitated a comprehensive exploration of students' perspectives regarding pedagogical strategies and their enthusiasm for learning. Table I presented below displays the questionnaire items employed in this research study.

Table I presents the questionnaire items used in the research to evaluate the respondents' perceptions of pedagogical strategies and their interest in learning. Respondents were asked to rate each question on a Likert scale ranging from 1 to 5, where 1 represents strong disagreement and 5 indicates strong agreement [7].

B. Validity Test

To assess the validity of respondents' perceptions regarding the influence of pedagogical strategies on students' learning interest, a two-tailed t-test was conducted. The choice of the two-tailed t-test as the statistical approach is based on its common use in evaluating the credibility of questionnaire responses and detecting significant differences between two datasets [17]. This method is essential in the context of questionnaire validation, ensuring the appropriateness of the questionnaire items in capturing their intended constructs [18].

With a chosen confidence level of 95% and a sample size of 100 respondents, a t-critical value of approximately 1.98, based on the t-distribution table, was computed. This critical value was subsequently utilized to evaluate the t-statistic obtained from the mean responses to questions 1 through 8 provided by the respondents. The results of this two-tailed t-test, conducted on the dataset, are presented in Table II.

TABLE I
QUESTIONNAIRE QUESTIONS

Aspect	Subject	Question
Pedagogical Strategies	Teaching Techniques	To what extent do you agree that teachers use a variety of teaching techniques to enhance your learning experience across different subjects?
	Visual Media Usage	How much do you feel that teachers effectively incorporate visual media (such as videos or pictures) into their lessons to support your understanding of various subjects?
	Technology Usage	To what extent do you agree that teachers use technology in their teaching to enrich the learning experience in different subjects?
	Practical Activities	How much do you feel that teachers organize practical activities and tasks to facilitate understanding and usage of subject-specific concepts and knowledge?
	Project-Based Methods	To what extent do you agree that teachers implement project-based methods to facilitate your learning in various subjects?
	Inclusive Learning Environment	How much do you feel that teachers create an inclusive and supportive learning environment in their classes across different subjects?
	Active Class Discussions	To what extent do you agree that teachers facilitate active class discussions to promote learning across different subjects?
	Interactive Learning Time	How much do you feel that teachers allocate enough time for interactive and practical learning experiences in their classes across various subjects?
Learning Interest	Interest in Real-World Applications	How interested are you in exploring the real-world applications related to the subjects you are learning?
	Encouragement of Independent Research and Self-Directed Learning	To what extent do you agree that teachers encourage independent research and self-directed learning in your studies across different subjects?

TABLE II
TWO-TAILED T-TEST RESULT

Aspect	Mean
Pedagogical Strategies	3.851
Learning Interest	3.515
Observations	100
Pearson Correlation	0.679
df	99
t Stat	6.586
P(T<=t) two-tail	2.18772E-09
t Critical two-tail	~1.98

The outcomes of the two-tailed t-test provide compelling evidence, indicating a statistically significant disparity in mean responses between the sections of our questionnaire pertaining to Pedagogical Strategies and Learning Interest. Furthermore, the Pearson correlation underscores a positive relationship between the concepts of pedagogical strategies and learning interest. These findings lend robust support to the questionnaire's validity. The pronounced statistical significance strongly suggests that the questionnaire items, which pertain to pedagogical strategies and learning interest, effectively capture the constructs they were designed to evaluate. Consequently, we deduce that pedagogical strategies wield a noteworthy influence on learning interest, as corroborated by the substantial evidence derived from the t-test results.

C. Reliability Test

The reliability test of a questionnaire is a crucial step in research, aimed at verifying that the questionnaire instrument consistently produces consistent and stable results when administered to the same individuals under identical conditions. This process is integral to ensuring the reliability of the questionnaire and the dependability of the data it generates.

In this study, we employed Cronbach's Alpha as the reliability measure for evaluating the questionnaire results. Our initial step involved calculating the total responses per respondent and the variance associated with each response to the questionnaire items. Subsequently, we computed the total variance, and, along with the total number of responses per respondent and the overall sample size, these values were integrated into the following equation [19]:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum \sigma_i^2}{\sigma_x^2}\right) \quad (1)$$

Where:

α = the Cronbach's alpha reliability value

k = the number of data in the measurement instrument

σ_i^2 = the variance between items (variance of individual items)

σ_x^2 = the total variance of scores from all items in the measurement instrument

Utilizing (1), we derived a Cronbach's Alpha coefficient of 0.825958849. In accordance with the standard Cronbach's alpha interpretation, where values less than 0.6 suggest low reliability, values in the range of 0.6 to 0.7 indicate moderate reliability, values from 0.7 to 0.8 signify reasonably good reliability, values from 0.8 to 0.9 represent high reliability, and values exceeding 0.9 indicate very high reliability [20], our obtained value falls into the high reliability category. Consequently, we can affirm that the questionnaire responses demonstrate a high degree of reliability, rendering them suitable for use as a classification dataset.

D. Model Design

In this section, we detail the design and methodology employed in our study. Our research required the application of advanced machine learning techniques, with a primary focus on leveraging Support Vector Machines (SVM). Previous questionnaire-based classification studies have consistently demonstrated the versatility of SVMs across various domains, including applications such as assessing piano teaching quality [21], analyzing engineering students' preferences for learning media [22], predicting student well-being based on stress and sleep questionnaires [23], investigating factors associated with hallux valgus [24], and assessing innovation management within recycling product contexts [25]. These exemplary use cases underscore the adaptability of SVMs in addressing classification tasks driven by questionnaire data.

In this study, we harnessed the SVM algorithm in conjunction with a linear kernel, a strategic choice with inherent advantages. This selection streamlines the process of parameter tuning, simplifying model configuration [26]. Furthermore, SVM with a linear kernel is acknowledged for its robustness when dealing with previously unseen data [27]. These attributes collectively position SVM with a linear kernel as a promising choice for our classification objectives.

For our analysis, we utilized responses obtained from questionnaires as our dataset. This dataset comprises eight features, denoted as P1, P2, P3, P4, P5, P6, P7, and P8, each corresponding to a specific question number (ranging from 1 to 8). To create the target variable, we categorized responses into 'Interested' and 'Not Interested' groups. This categorization was determined by computing the average of respondent answers to questions 9 and 10. The Likert scale served as a reference, where an average value below 3 signified 'Not Interested,' while an average value of 3 or above was assigned to the 'Interested' category.

E. Performance Evaluation

To assess the performance and generalizability of our classification model, a rigorous 10-fold cross-validation approach will be employed. This technique involves dividing our dataset into ten subsets or "folds." The model will be trained and evaluated ten times, with each fold serving as the test set once and the remaining nine as the training set. This process is repeated, allowing each subset to be used as the test set. The results are then averaged to provide a comprehensive assessment of the model's predictive capabilities.

The following performance metrics will be utilized to evaluate our model:

1. Area Under the Receiver Operating Characteristic (ROC-AUC)
   ROC-AUC is a measure of the model's ability to distinguish between "Interested" and "Not Interested" categories. It assesses the trade-off between true positive rate (sensitivity) and false positive rate.
2. Classification Accuracy (CA)
   CA quantifies the proportion of correctly classified instances in our dataset. It provides an overall measure of our model's accuracy.
3. Precision
   Precision evaluates the model's ability to correctly classify instances as "Interested." It measures the ratio of true positives to the total number of instances classified as "Interested."
4. Recall (Sensitivity)
   Recall assesses the model's capability to correctly identify all "Interested" instances, measuring the ratio of true positives to the total number of actual "Interested" instances.

This comprehensive evaluation approach allows us to gauge the model's predictive performance, assess its ability to discriminate between categories, and identify its strengths and weaknesses. It ensures that our classification model is both reliable and generalizable, supporting robust conclusions for our research.

F. Feature Analysis

Feature analysis is a fundamental aspect of our methodology, and we have chosen to employ permutation evaluation to assess the significance of individual features within our model. This section elucidates our method, the permutation feature importance, for scrutinizing the importance of each feature, providing insights into the key drivers behind our research findings. The permutation feature importance (PFI) is a popular method for measuring the importance of each feature in a dataset [28]. This method is used to determine the significance and importance of each feature in the context of model performance, by identifying which features have the most substantial impact on the model's predictions and is a valuable technique for feature selection and understanding feature contributions [29]. PFI involves systematically assessing the influence of individual features on a machine learning model's performance [30].

The process begins by selecting one feature at a time from the dataset and creating a perturbed dataset where the values of the chosen feature are randomly shuffled. The original model is then used to make predictions on this perturbed dataset, and the change in model performance is measured using a performance metric. The impact of each feature is quantified by comparing model performance between the perturbed and original datasets. Features with a significant drop in performance when permuted are considered important, while those with minimal impact are deemed less influential [31].

In the permutation evaluation process, we systematically analyze the mean and standard deviation of each feature's impact on the model's performance. By permuting or shuffling the values of each feature while keeping the target variable intact, we can assess the extent to which a feature contributes to the model's predictive accuracy. This analysis helps identify key variables that drive the model's predictions and informs feature selection and interpretation.

III. Result and Discussion

In the following section, we present the results and discussion of our study, starting with an overview of performance metrics and subsequently delving into the analysis of the confusion matrix and feature importance scores, shedding light on the model's classification capabilities and the significance of individual features.

TABLE III
PERFORMANCE RESULT

AUC	CA	Precision	Recall
93.3	95	95.3	95

The discriminative power of the model was assessed using the Area Under the Curve (AUC) metric, which yielded an AUC value of 93.3%. This AUC score is indicative of a model with robust discriminatory capabilities, signifying its ability to effectively differentiate between the two distinct classes with a substantial degree of confidence.

Furthermore, the model's overall classification performance was evaluated using additional key metrics. The Classification Accuracy (CA) was observed to be notably high, registering at 95%. This CA score reflects the model's capacity to make accurate predictions for the majority of the instances, attesting to its proficiency in classifying data points correctly. In-depth scrutiny of the model's precision reveals a remarkable value of 95.3%. Precision, a measure of the model's ability to correctly identify positive instances when predicting the positive class, underscores the model's proficiency in minimizing false positives. This exceptional precision score reinforces the model's capability to make highly accurate positive class predictions. Moreover, the model's ability to capture actual positive instances was examined through the metric of Recall, which was found to be 95%. The high recall score indicates the model's competence in identifying and correctly classifying the vast majority of positive cases, reflecting a strong aptitude for recognizing positive instances.

Overall, the model's performance across these metrics is undeniably commendable. It exhibits a high AUC, a CA that points to accurate predictions, precision marked by a low rate of false positives, and robust recall capabilities. These findings collectively affirm the model's excellence in classification tasks, solidifying its potential for a wide range of applications. However, it is crucial to consider the specific context of the application and class distribution to ascertain the model's suitability for the intended purpose. Furthermore, validation of model performance on a distinct test dataset is recommended to confirm its ability to generalize effectively to new, unseen data.

TABLE IV
CONFUSION MATRIX TABLE

	Interested	Not Interested
Interested	87	3
Not Interested	2	8

From the viewpoint of the "Interested" class, the model has demonstrated commendable performance. It correctly identified 87 individuals as "Interested," showcasing its robust capability to accurately classify those expressing genuine interest. However, a noteworthy aspect is that the model did falter in a few instances, misclassifying 3 individuals as "Not Interested" when they were, in reality, "Interested." These 3 false negatives underline situations where the model failed to correctly identify individuals with genuine interest. Such instances are particularly critical, as any failure in recognizing "Interested" individuals might have substantial consequences.

Turning to the "Not Interested" class, the model's performance is also favorable. It succeeded in accurately recognizing 8 individuals as "Not Interested," underscoring its proficiency in distinguishing those who genuinely lack interest. Nevertheless, there were instances of 2 false positives, where the model incorrectly categorized individuals as "Interested" when they were, in fact, "Not Interested." These 2 false positives emphasize cases in which the model's predictions were inaccurate and could potentially result in unwarranted actions or costs.

In summation, the model exhibits notable strength in correctly classifying individuals in both the "Interested" and "Not Interested" categories. While it excels in identifying "Interested" individuals, as evidenced by a substantial count of true positives and a low count of false negatives, there is room for refinement in mitigating false positive predictions, particularly those instances where "Not Interested" individuals are erroneously classified as "Interested." Enhancing the model's precision in classification is of paramount importance, particularly in scenarios where erroneous classifications may yield adverse consequences or resource expenditures.

TABLE V
FEATURE IMPORTANCE SCORES

Feature	Mean	Standard Deviation
P1	0	0.006324
P2	0.004	0.004898
P3	0.004	0.008
P4	0.052	0.014696
P5	0.022	0.016
P6	0.082	0.01939
P7	0.058	0.023151
P8	0.006	0.004898

This research has explored the pivotal role of feature importance analysis, emphasizing the "Mean" and "Standard Deviation" metrics, in enhancing our understanding of predictive models. The "Mean" metric elucidates the average importance of each feature, offering insights into its impact on the model's predictive performance, while the "Standard Deviation" metric reveals the degree of variability in importance scores, providing valuable information about the consistency of feature contributions. These findings carry direct implications for feature selection, model optimization, and the broader comprehension of predictive modeling, thereby facilitating more informed decision-making in the realm of machine learning and data-driven research.

The assessment of feature importance within the context of the model's predictive performance unveiled notable insights. Features with elevated mean importance scores, specifically P6 (0.082) and P7 (0.058), demonstrated a substantial influence on the model's predictive capabilities. These features exhibited a strong impact, underlining their significant contributions to the model's overall performance. Conversely, features with lower mean importance scores, such as P1 (0), P2 (0.004), and P3 (0.004), were found to have a more limited impact on the model's predictions. Notably, P1 registered an importance score of 0, indicating a lack of influence in the predictive process. This feature-specific analysis provides a nuanced understanding of the factors that drive the model's predictions and offers valuable guidance for feature selection and model refinement.

The evaluation of feature importance revealed a diverse landscape characterized by both mean importance scores and standard deviations. Features characterized by low standard deviations, exemplified by P1, P2, and P3, consistently maintained importance scores; however, these scores tended to be relatively modest, suggesting their limited influence on the model's predictive performance. In contrast, features exhibiting higher standard deviations, such as P4, P5, P6, and P7, displayed more pronounced variability in their importance scores. These features, despite their variability, boasted higher mean importance scores, underscoring their substantial impact on the model's predictive outcomes. Notably, P8 was distinguished by its consistent importance score, but this score remained comparatively low, signifying a consistent yet modest contribution to the model's overall predictive performance. This comprehensive feature-specific analysis provides valuable insights into the nuanced interplay of stability and influence among individual features, offering critical guidance for feature selection and model optimization.

Within the spectrum of feature importance metrics, P6 emerged as a standout with a notably high mean importance score of 0.082, signifying its pivotal role as an influential feature with a significant impact on the classification target. Importantly, this feature displayed a low standard deviation (0.01939), indicating a remarkable degree of stability in its importance across multiple iterations, further underlining its reliability in driving model predictions. Similarly, P7 exhibited a relatively high mean importance score of 0.058, indicating its importance in the classification process. While it featured a slightly higher standard deviation (0.023151), suggesting a marginally higher degree of variability, it remained a robust and stable contributor to the model's predictive performance. Collectively, these findings spotlight the pivotal roles played by P6 and P7, emphasizing their balanced attributes of influence and stability. These two features are poised to exert a more substantial impact on the classification target compared to the remaining features, thus holding significant promise in enhancing the model's overall performance.

This research offers a comprehensive assessment of the model's classification performance, insights into the confusion matrix from the perspective of the target classes, and a detailed analysis of feature importance. These findings collectively contribute to the understanding of the model's capabilities and offer guidance for its refinement and optimization. The model's strong classification metrics, combined with feature-specific insights, underline its potential for a wide array of practical applications.

IV. Conclusions

In conclusion, this research has made significant strides in the realms of education and machine learning. We embarked on a distinctive journey to investigate the impact of pedagogical strategies on students' learning interest, focusing on eight distinct dimensions of pedagogical strategies. By employing a classification approach using machine learning, we have enhanced our understanding of the intricate relationship between teaching techniques and students' enthusiasm for learning. Our research not only provides actionable insights for educators, institutions, and policymakers but also introduces a novel approach to dissect the relative importance of these strategies.

The rigorous research methodology, from data collection and validity tests to reliability analysis and model design, has ensured the credibility and stability of our dataset. The employment of Support Vector Machines with a linear kernel has showcased the model's robustness and adaptability in the context of questionnaire-based classification studies. The high performance metrics, including a strong AUC, Classification Accuracy, Precision, and Recall, underscore the model's excellence in accurately categorizing students' learning interests.

Feature analysis has shed light on the key drivers behind our research findings, highlighting the significant influence of certain pedagogical strategy dimensions, particularly P6 and P7. These dimensions have consistently demonstrated a substantial impact on the model's predictive performance, offering valuable insights for feature selection and model optimization.

This research serves as a cornerstone for future investigations into the dynamics of pedagogical strategies and their profound impact on students' learning interest. It provides a robust framework for creating more engaging and effective learning environments, ultimately benefiting both educators and students. Through our comprehensive approach, we have not only advanced the understanding of pedagogical strategies but also showcased the potential of machine learning in educational research.

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