Impact of The Covid-19 Pandemic on Student Learning Styles: Naïve Bayes and Decision Tree Classification in Education

Zaqi Kurniawan [1]*, Rizka Tiaharyadini [2]
Program Studi Teknik Informatika, Fakultas Teknologi Informasi Universitas Budi Luhur [1], [2]
Jakarta, Indonesia
zaqi.kurniawan@budiluhur.ac.id [1], rizka.tiaharyadini@budiluhur.ac.id [2]

Abstract - **The Covid-19 pandemic significantly changed education with social distancing and changes in the learning environment. In this study, one strong reason for the significance of the research is the urgency of changes in students' learning styles during the Covid-19 pandemic. Investigating differences in learning styles before and during the pandemic not only provides deep insight into students' adaptation to these changes, but also provides a foundation for the development of more inclusive and adaptive learning strategies in the future. This study aims to analyze the effect of the Covid-19 pandemic on students' learning styles in an educational context, focusing on the comparison of two classification methods, Naïve Bayes and Decision Tree. The study was conducted by collecting data on students' learning styles before and during the Covid-19 pandemic, using various relevant indicators. The data was obtained based on school survey results and online platforms, involving student characteristics and learning preferences. The data was then analyzed using Naïve Bayes and Decision Tree classification methods to identify significant changes in students' learning styles. The results showed the prediction accuracy of learning style changes with Naïve Bayes 68.75% and Decision Tree 87.50%. Recommendations for educators and education policy makers are to develop inclusive and adaptive learning strategies to meet diverse learning preferences.**

Keywords— **Covid-19 Pandemic, Student Learning Styles, Classification Methods, Naïve Bayes, Decision Tree**

I. INTRODUCTION

The Covid-19 pandemic has had a major impact on the global education system, with a significant transition towards distance education[1]. Students' preferred methods of learning as well as the efficiency of the educational process have been significantly impacted by these modifications. Several steps have been taken during this epidemic to alter teaching and learning strategies, including as delivering subject content using digital technologies[2]. During the pandemic, many students faced social isolation, which may have had an impact on their mental health. For this reason, kids' psychosocial assistance needs to receive extra consideration[3]. Teachers must be adaptable in their approach to meet the needs of students with different learning styles [4]. Teachers now have to adjust to virtual learning environments, which might restrict their comprehension of how kids study at home. Studies reveal that 52% of student accomplishment is attributed to their learning styles [5]. The primary research problems may revolve around understanding the specific alterations in student learning styles caused by the Covid-19 pandemic [6]. These problems might include investigating how remote or hybrid learning environments have affected student engagement, behavioral patterns, and academic performance [7].

Additionally, identifying the effectiveness of various teaching methods or instructional approaches during the pandemic-induced changes in educational settings could be another key research problem [8]. Overall, the research problems within this study may encompass elucidating the pandemic's direct influence on student learning styles, evaluating the efficacy of educational methods amid disruptions, and comprehending the factors that shape students' adaptability in evolving learning environments [9].

The aim of the research is to develop a technologically advanced system that analyzes how the Covid-19 pandemic has impacted student learning habits by utilizing Naïve Bayes and Decision Tree algorithms. This approach looks at a lot of data regarding student behavior and academic performance during remote or hybrid learning in an effort to give educators insights into how to adapt curricula and teaching strategies to meet changing demands of students in changing educational environments [10]. The proposed system would use these cutting-edge machine learning techniques to examine large-scale datasets covering student behavior, engagement trends, and academic achievement in a variety of learning environments—particularly amid the interruptions brought on by the epidemic [11].

Naïve Bayes and Decision Tree algorithms will play a pivotal role in this research by providing the means to discern intricate shifts in learning preferences, adaptability to diverse educational settings, and the effectiveness of different instructional approaches experienced by students throughout the pandemic period [12]. With the use of these techniques, the study hopes to provide specific insights into how these

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algorithms might correctly identify and forecast shifts in learning styles, enabling educators and decision-makers to effectively modify curricula and teaching strategies to meet students' changing needs in the face of pandemic-related educational challenges that have never before been seen.

Previous research investigating the pandemic's effects on students' learning styles frequently ignored specific, unique learning style changes in favor of broad, general patterns [13]. Previous research examining the effects of the Covid-19 pandemic on student learning styles has provided valuable insights into the broader shifts in educational paradigms [14]. The novelty of this research lies in its application of Naïve Bayes and Decision Tree algorithms to discern these nuanced changes with a high level of precision. By employing these advanced classification methods, this study aims to surpass prior research by providing a more detailed and accurate understanding of the alterations in student learning styles caused by the pandemic.

This study aims to further the current body of knowledge by applying Naïve Bayes and Decision Tree algorithms in a more concentrated and comprehensive way than other works with similar titles and methodology. This research project aims to provide a more detailed and accurate picture of how the pandemic has affected and changed certain student learning preferences and behaviors by utilizing these comprehensive classification techniques. The new aspect of this research is how thorough and accurate it is, enabling a thorough investigation of different learning styles and how they have been adjusted in different educational settings throughout the Covid-19 upheavals.

Naïve Bayes is a probabilistic classification method known for its simplicity and efficiency in handling large datasets [15]. Based on a variety of characteristics, including behavior patterns, engagement measures, and performance indicators, Naïve Bayes can help classify and predict changes in student learning styles in the context of this research. Decision tree classification, on the other hand, is useful because it can identify complex patterns and correlations in large, complicated datasets [16]. Decision Tree methods, when used in this study, can help determine the precise characteristics or aspects that have a major impact on changes in students' learning styles brought on by the Covid-19 epidemic.

The decision tree and naïve bayes methods combine effectively together because they offer a thorough analysis that helps to clarify the complex ways that students' learning, settings, and adaptations have changed as a result of these difficult situations. When combined, these algorithms can help in the discovery of complex aspects of how the pandemic has affected students' learning structures. This information helps policymakers and educators create specific strategies of action to address the shifting needs of education in the post-pandemic period.

The goal of this study is to compare and evaluate the prediction results of these two algorithms in order to assess the benefits and drawbacks of each strategy for predicting changes in students' learning styles after Covid-19. Through gaining a deeper knowledge of the algorithms' performance, educators may make better decisions when developing teaching methods that adapt to students' wants and needs in the aftermath of the epidemic.

II. RESEARCH METHOD

This study uses two supervised learning methods—Naïve Bayes and Decision Trees—to conduct a prediction analysis [17]. An further description of the study approach will be provided in the following sub-chapter, as shown in Figure 1. This study's predictive analytic approach enables the authors to anticipate potential shifts in students' preferred learning styles following the Covid-19 outbreak and to extract useful information from the educational data that is now available. The next part will include a thorough explanation of the research methodology, giving readers a deeper knowledge of the procedures used in this study.

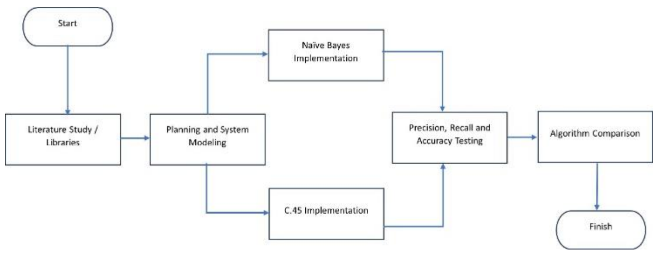

Fig.1.Research Metodology

A. Literature Review

The literature review for this study looks at research about how the Covid-19 pandemic has impacted education. It focuses on how schools had to adapt, moving to online or hybrid learning, and the challenges they faced. It also examines how students' participation and grades changed during this time. The review includes studies on how people learn and different theories about learning styles. It also looks at previous research that used Naïve Bayes and Decision Tree algorithms in education [18]. Additionally, it explores how machine learning is used in classrooms, especially in understanding how students learn. The goal of this review is to understand all these areas of research, find any missing information, and suggest using Naïve Bayes and Decision Tree algorithms to study how the pandemic affected the way students learn.

B. Dataset

The dataset for the study was collected from various educational sources during the Covid-19 pandemic, encompassing student behaviors, academic performance, engagement metrics, and demographics. It includes variables like learning preferences, study habits, online class participation, test scores, assignments, and interactions with educational materials. Moreover, it includes demographic factors like age, gender, geographical location, and socio-economic backgrounds to examine potential correlations between these variables and changes in learning styles. The dataset aims to capture the intricate changes in student

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learning behaviors and preferences amidst the Covid-19 pandemic.

B. Designs and Models

The design of the study employs a comprehensive methodology that integrates the Naïve Bayes and Decision Tree classification methods. The changes in student learning styles during the epidemic are investigated using the probabilistic model Naïve Bayes and the data categorization method Decision Tree [19]. These models are used to a wide range of factors in order to classify and forecast changes in learning preferences. In order to provide a better understanding of how the pandemic has affected different learning styles, the design focuses on utilizing these sophisticated models to identify complex trends in student behavior, engagement metrics, and academic achievement.

C. Naïve Bayes Method

Based on Bayes' theorem and assuming the "naïve" premise of predictor independence, Naïve Bayes is a traditional and simple probabilistic classification technique [20]. According to this approach, the existence of a certain feature inside a class is independent of the existence of other characteristics. In many classification applications, Naïve Bayes works well despite its naive assumptions; this is especially true for text categorization, spam filtering, and natural language processing [21]. Large datasets are easily handled by it, and its low processing needs make it quite effective [22]. This method is a powerful and popular tool for classification and prediction tasks in several fields since it determines the likelihood of an event occurring given the presence of specific characteristics. Equation 1 below illustrates how the Naïve Bayes method may be used to analyze the gathered data and create a prediction model

$$(H|X) = \frac{P(X|H) \cdot P(H)}{P(X)} \tag{1}$$

D. Decision Tree Method

Decision Tree is a popular machine learning algorithm used for both classification and regression tasks [23]. It operates by recursively partitioning the dataset into smaller subsets based on the most significant attribute or feature that best separates the data. The goal is to create a tree-like structure where each internal node represents a feature, each branch represents a decision rule, and each leaf node corresponds to a class label or numerical value. The algorithm selects the best attribute to split the data by evaluating various attributes using metrics like Gini impurity or information gain [24].

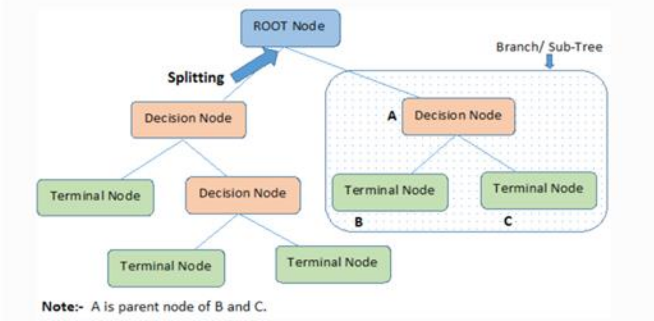

Fig.2.Decision Tree Method

E. Implementation of C.45

C4.5, also known as C5.0, is a popular decision tree algorithm used in machine learning for classification tasks [25]. By dividing datasets according to attribute values, it creates decision trees by categorizing instances into distinct groups. Information gain and gain ratio are two examples of the elements that C4.5 takes into account while choosing the optimal characteristics to divide [26]. It uses statistical techniques to account for missing values and can handle both continuous and discrete data properties. C4.5 is simple to understand and analyze, but it may overfit complicated data. The formula for calculating gain and entropy is as follows:

$$Entropy(S) = \sum_{j=1}^{k} = pj \log 2\, pj \tag{2}$$

In equation (2) above is the equation used in calculating the entropy value to determine the heterogeneity (differences in characteristics or properties between individuals) of a sample data set.

$$Gain(A) = Entropy(S) = \sum_{j=1}^{k} \frac{|Si|}{|S|} x Entropy(Si) \tag{3}$$

Understanding the aforementioned equation enables one to utilize the C.45 method to enter and process data for the decision tree creation process.

F. Algorithm Testing

A subset of the dataset called the test set, which was not used for training, is usually used to test these algorithms. With this test set, the algorithms are used to forecast the learning styles of the students by using the features and patterns they were taught during training. Performance metrics such as accuracy, precision, recall, and F1-score are commonly used to assess how well the algorithms classify student learning styles compared to the actual observed learning styles in the test data [27]. The purpose of this testing phase is to ascertain if the Naïve Bayes and Decision Tree algorithms are reliable and successful in properly classifying and forecasting the learning styles of students. This will provide light on how the Covid-19 epidemic has affected educational approaches. Further details about the dataset design can be seen in Table 1 below.

Table 1. Design of Research Dataset

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Learning Styles	Learning Condition Before The Pandemic	Learning Outcomes Before The Pandemic	Learning Outcomes After The Pandemic	Post - Pandemic Learning Conditions
Visual	Good	85	87	Increasing
Auditory	Good	78	80	Increasing
Kinesthetic	Less	60	55	Decreasing

III. RESULT

A model that makes it easier to compare Decision Tree and Naïve Bayes algorithms and assesses their performance based on precision, recall, and accuracy scores is one of the research's outputs. As mentioned by [28] assessing algorithm effectiveness requires specific standards and tools. Calculating precision, recall, and accuracy numbers is necessary for comparing the Decision Tree and Naïve Bayes approaches in order to identify the most effective algorithm. The data was divided into two categories during the first testing phase: data-training, which provided the foundation for each algorithm's calculations, and data-testing, which assessed how accurately the algorithms predicted and made judgments. Equation 4, which is displayed below, computes precision and determines the percentage of accurate situations [29].

$$\mathrm{Pr}\,ecision = \frac{TP}{TP + FP} \tag{4}$$

Equation 5 defines recall as the precise determination of the proportion of affirmative cases. Similarly, accuracy—which is represented by Equation 6—determines the percentage of accurate forecasts among all of the guesses.

$$\mathrm{Re}\,call = \frac{TP}{TP + FN} \tag{5}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{6}$$

A. Evaluating Precision, Recall, and Accuracy on Naïve Bayes Method

The precision, recall, and accuracy test results on datasets labeled with post-pandemic learning conditions are shown in this section (refer to Tables 2). Based on the accuracy, precision, and recall results for the Naïve Bayes model, when predicting an increase in student learning styles, the model correctly identified an actual increase 37 times, and when predicting a decline, it correctly identified the decline 16 times, resulting in a class precision of 69.81%. Conversely, for predictions indicating a decrease in learning styles, the model accurately predicted a decline nine times, and when predicting stability, it correctly identified stability 38 times, yielding a class precision of 80.85%.

Moreover, the class recall for true increases was 80.43%, and for true decreases, it was 70.37%. These findings suggest that the Naïve Bayes model demonstrated moderate precision rates for both predicting increases and decreases in learning styles. However, it showed a higher precision for predicting a decrease compared to predicting an increase. The recall rates indicate that the model was relatively better at correctly recalling instances of actual increases in learning styles compared to true decreases, signifying a relatively better performance in identifying instances of actual increases in learning style

Table 2. Summary of Accuracy, Precision, and Recall Naïve Bayes Method Test Results on Post-Pandemic Learning Dataset

	True Increase	True Decrease	Class Precision
Predicted Increase	37	16	69,81 %
Predicted Decrease	9	38	80,85 %
Class Recall	80,43 %	70,37 %	

B. Evaluating Precision, Recall, and Accuracy on Decision Tree Method

Based on the accuracy results for the Decision Tree model, when predicting an increase in student learning styles, the model correctly identified an actual increase 42 times, and when predicting a decline, it correctly identified the decline five times, resulting in a class precision of 89.36%. On the other hand, for predictions indicating a decrease in learning styles, the model accurately predicted a decline four times, and when predicting stability, it correctly identified stability 49 times, yielding a class precision of 92.45%. Additionally, the class recall for true increases was 91.30%, and for true decreases, it was 90.74%. These outcomes suggest that the Decision Tree model performed well in identifying both increases and decreases in learning styles, displaying high precision rates for predicting both an increase and a decrease. Moreover, the recall rates indicate that the model effectively recalled instances of actual increases and decreases in learning styles, showing a balanced performance in identifying both classes with high accuracy

Table 3. Summary of Accuracy, Precision, and Recall Decision Tree Method Test Results on Post-Pandemic Learning Dataset

	True Increase	True Decrease	Class Precision
Predicted Increase	42	5	89,36 %
Predicted Decrease	4	49	92,45 %
Class Recall	91,30 %	90,74 %	

B. Simple Distribution Naïve Bayes Method

For the auditory learning style, the density is 0.28 for an increase and 0.32 for a decrease. In the kinesthetic learning

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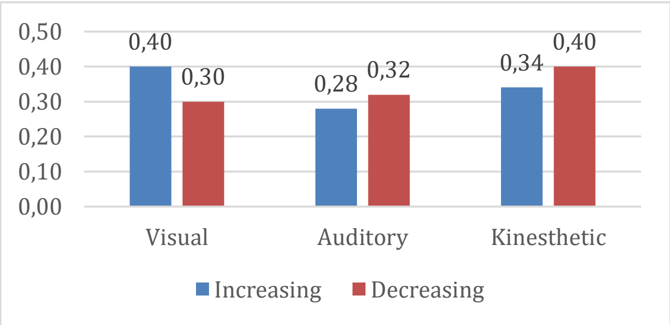
style, the density measures 0.34 for an increase and 0.40 for a decrease. Lastly, for the visual learning style, the density is 0.40 for an increase and 0.30 for a decrease. These density values suggest varying degrees of change in learning styles under different conditions.

The auditory style shows a relatively smaller density change between increase and decrease compared to kinesthetic and visual styles. Kinesthetic style exhibits a slightly higher density change between the two conditions, with the visual style displaying the most notable density shift between increase and decrease. This indicates that the visual learning style experiences a more pronounced change compared to auditory and kinesthetic styles when transitioning between increase and decrease scenarios, highlighting potential differences in how these learning styles adapt or fluctuate in response to changing conditions . This distribution is seen in Graph 1.

Graph 1. Simple Distribution Naïve Bayes Method



C. Performance Vector for Naïve Bayes Method

The ROC values intersecting the x and y-axis are as follows: 0.60 (0.00 - 0.20), 0.65 (0.20 - 0.25), 0.75 (0.25 - 0.40), 0.85 (0.40 - 0.50), 0.90 (0.50 - 0.60), 0.95 (0.60 - 0.75), and 1.00 (0.75 - 1.00). These values indicate the trade-off between the true positive rate (sensitivity) and false positive rate (1-specificity) at various thresholds. Analyzing the curve, as the ROC value increases from 0.60 to 1.00, there is a noticeable improvement in the model's performance. The ROC curve is closer to the upper-left corner, indicating better discrimination between true positive and false positive rates.

The AUC value, representing the overall performance, tends towards 1.00, indicating a higher ability of the Naive Bayes model to correctly classify instances. The higher the AUC value, the better the model's ability to distinguish between classes. Regarding optimal classification, the Naive Bayes model seems to perform well with an AUC value of approximately 1.00, which suggests near-perfect classification. This implies that the Naive Bayes model is highly effective in distinguishing between the classes, achieving an optimal level of classification accuracy at around 95% or higher based on the AUC value. This curve is seen in Fig 3.

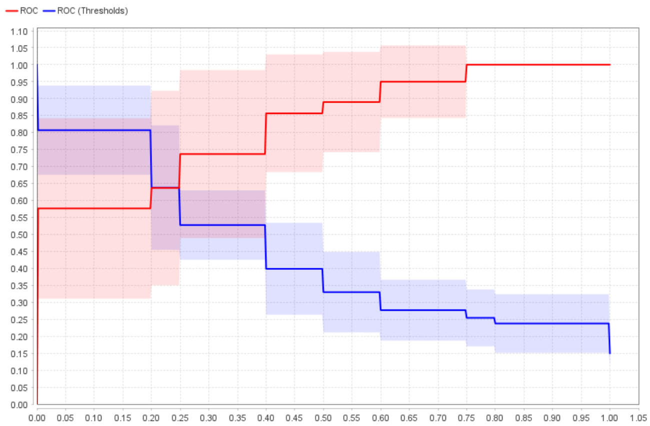


Fig.3. AUC and ROC Curve for Naïve Bayes Method

D. Performance Vector for Decision Tree Method

The ROC values corresponding to the x and y-axis are: 0.8 (0.20), 0.9 (0.25), and 1.0 (0.25 to 1.00). These values illustrate the relationship between true positive rate (sensitivity) and false positive rate (1-specificity) at various thresholds. Analyzing the curve, the Decision Tree model demonstrates strong performance, as indicated by the ROC values. As the ROC value progresses from 0.8 to 1.0, the curve tends towards the upper-left corner, suggesting improved discrimination between true positive and false positive rates.

The AUC (Area Under the Curve) value represents the overall performance of the model. An AUC value of 1.0 suggests perfect classification, showcasing the model's ability to distinguish between the classes with high accuracy. Regarding the optimal classification, the Decision Tree model seems to perform exceptionally well with an AUC value of 1.0, indicating near-perfect classification. This suggests that the Decision Tree model achieves optimal classification accuracy, approximately 100%, based on the AUC value, signifying an excellent ability to differentiate between classes. This curve is seen in Fig 4.

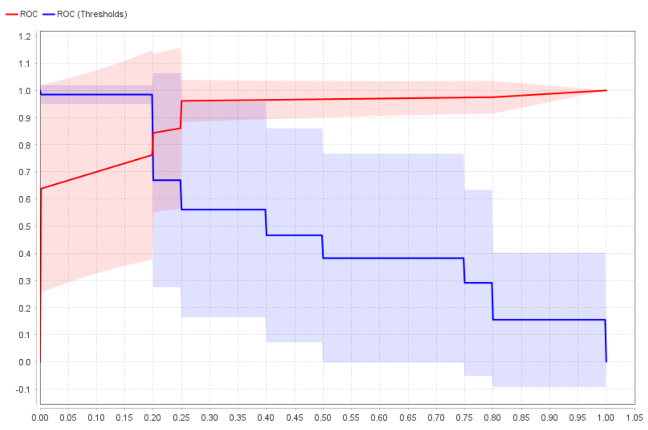


Fig.4. AUC and ROC Curve for Decision Tree Method

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IV. DISCUSSION

The efficiency of models, system design, and the opportunities and problems they provide are all covered in detail in this section. It thoroughly looks at how effectively models function, the systems' architectural design, the challenges that arise, and potential for future advancement.

A. Model Effectiveness

The models, Naïve Bayes and Decision Tree, demonstrate strong effectiveness in classifying student learning styles. Naïve Bayes exhibits moderate precision in predicting both increase and decrease in learning styles, with better precision for declines. It displays higher recall for increases, suggesting a relatively better performance in identifying actual increases in learning styles. The Decision Tree model showcases high precision rates for both increase and decrease predictions, along with balanced and accurate recall rates for both scenarios.

Additionally, the models display near-perfect discrimination between true and false positives, as indicated by their respective AUC values. Naïve Bayes approaches an AUC of 1.00, implying near-perfect classification accuracy of around 95% or higher, while the Decision Tree achieves an optimal AUC of 1.0, indicating almost flawless classification accuracy of approximately 100%. Both models effectively differentiate between learning style classes, demonstrating strong effectiveness in classifying student learning behaviors

B. Systems Designs

One of the most important aspects of contemporary education is the system design for analyzing how the Covid-19 epidemic has affected students' learning patterns. Using two categorization techniques—Naïve Bayes and Decision Tree—this system design methodology assesses how students' learning styles changed during the epidemic. Referring to [29/28] research, the use of Naïve Bayes algorithms proved their ability to classify and analyze data with high accuracy in the context of online learning.

Moreover, as the research by [31] emphasizes, the Decision Tree has become a useful instrument for comprehending differences in learning styles brought about by the pandemic's impact on educational paradigms. Furthermore, research [32] demonstrates that a design system that combines both categorization techniques offers a more comprehensive picture of how well students adjust to distant learning. Alternatively, research by [33] highlights how crucial it is to take into account the unique characteristics of each student when using categorization methodologies in order to guarantee the appropriateness and long-term viability of instructional strategies. Additionally, as per [34], putting this system design into practice creates chances for creating more dynamic models that may adapt to students' evolving learning demands in the future.

C. Challenge and Opportunities

There are several opportunities and obstacles in education when examining how the Covid-19 epidemic has affected kids' learning patterns. As [35] explains, one of the difficulties is modifying instructional strategies to fit the changing environment. The shift in the educational process from conventional to online learning formats is necessary because it may have a big impact on how students learn [36]. Nevertheless, there are plenty of chances to incorporate technology into education even with these difficulties. One approach to more precisely and effectively examine changes in students' learning styles under the influence of the epidemic is to use classification algorithms like Naïve Bayes and Decision Tree [37].

Educational institutions may enhance their teaching techniques, better understand the requirements of their students, and adapt to the dynamic shifts in learning by embracing an innovative and inclusive approach. All things considered, the current state of education, while difficult, offers a chance to create fresh approaches that are more flexible and sensitive to the changing needs of students' learning styles in the future.

V. CONCLUSSION

The study's methodology utilizing Naïve Bayes and Decision Tree techniques effectively analyzed the impact of the Covid-19 epidemic on students' learning styles. Both models showcased proficiency in classifying learning behaviors, with Naïve Bayes displaying moderate precision and better recall for identifying increases, while the Decision Tree model demonstrated high precision and balanced recall for varied scenarios. The near-perfect discrimination between true and false positives, indicated by AUC values approaching 1.00 and 1.0 for Naïve Bayes and Decision Tree respectively, emphasizes the models' accuracy. This research presents an opportunity for educational institutions to adapt teaching methods, comprehend students' evolving needs, and embrace innovative, inclusive approaches. Despite the challenges posed by the pandemic, this study provides a platform for creating flexible strategies that align with the dynamic shifts in students' learning styles, promising a more adaptable and responsive educational system in the future.

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