Comparing Naïve Bayes and Decision Tree Classification Techniques in Educational Settings: An Examination of the Impact of The Covid-19 Pandemic on Student Learning Styles

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, social distancing, and changes in the learning environment. 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, namely 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

# 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]. This not only influences students' willingness to study, but also the quality of their learning results, as instructors face new hurdles [3]. The modern educational paradigm is requiring instructors and students everywhere to adjust. Keeping students engaged and ensuring they have a thorough comprehension of the material are just two of the additional problems that come with distance learning. Optimizing the remote learning experience requires innovative approaches to curriculum design and learning material production [4]. It's also important to take into account the social and emotional components of learning. During the epidemic, 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 [5].

 People receive information in different ways, and three types of learning styles exist: kinesthetic, auditory, and visual (V-A-K) [6]. Furthermore, it's critical to keep in mind that a person's preferred method of learning is not necessarily determined by their learning environment; rather, it might vary based on the particular situation. Teachers must be adaptable in their approach to meet the needs of students with different learning styles [7]. 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 [8].

 A method called "educational data mining" uses data modeling, machine learning, statistics, and educational expertise to find hidden patterns in system-generated data [9]. Based on the Bayes Theorem, Naïve Bayes is a quick and efficient classifier [10]. In decision making, decision tree algorithms—which categorize data samples based on feature values—are frequently employed [11]. The effect of the Covid-19 epidemic on learning style preferences has been studied in the past. For example, [12] discovering that learning accomplishment and the degree of discipline maintained during online instruction are positively correlated, with each element accounting for 19% of students' total learning achievement. Furthermore, research shows that students' motivation to participate in online learning has a major impact on both their academic progress and interest in learning [13]. This study is noteworthy since it makes use of both Naïve Bayes and Decision Tree approaches to predict and assess changes in students' learning styles during the Covid-19 pandemic..

 Using complex data analysis approaches, such as Decision Tree and Naïve Bayes, this research focuses on evaluating changes in student learning patterns following the Covid-19 epidemic. Our primary goal is to create prediction models that will allow for a thorough examination of educational data and help us comprehend how the Covid-19 epidemic could affect students' preferred learning styles. With the learning environment undergoing substantial changes, this research attempts to offer insightful information to educators, researchers, and stakeholders in education. Moreover, Rapidminer software is used in this study to assess how Naïve Bayes and Decision Tree algorithms are applied in this situation.

 This study compares and analyzes the prediction outcomes of these two algorithms in an effort to determine the advantages and disadvantages of each approach for foretelling shifts in students' learning styles after COVID-19. With a deeper knowledge of these algorithms' performance, educational practitioners may take more informed steps in building learning techniques that meet the requirements and preferences of students in the post-pandemic period.

# RESEARCH METHOD

 This study uses two supervised learning methods—Naïve Bayes and Decision Trees—to conduct a prediction analysis. [14]. 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

## Literature Review

 This study of the literature compiles pertinent hypotheses from earlier studies in an effort to provide a solid knowledge framework for our analysis of how student learning styles have changed since the Covid-19 outbreak. A thorough examination of the relevant literature was the first step in our research project. Comprehensive knowledge of data mining theory, Naïve Bayes, and Decision Tree algorithms, as well as testing techniques including accuracy, recall, and precision, were covered in this literature study.

*B. Designs and Models*

 Data collection, cleaning, management of missing or erroneous numbers, and formatting of the data to fit the selected technique are all included in this step. The chosen model must next be designed and put into practice. The process of evaluating and validating the model proceeds by measuring prediction accuracy, assessing performance, and contrasting the Naïve Bayes and Decision Tree approaches with test data that has been isolated from training data.

*C. Naïve Bayes Method*

 In [16]'s research, the Naïve Bayes method is examined, as [15] documented. Bayes Theorem and is notable for its uncomplicated methodology that eschews intricate parameter estimate procedures. Robustness, elegance, and simplicity. According to [17], the Naïve Bayes method is a good option for direct application to big datasets [18]. Equation 1 below illustrates how the Naïve Bayes method may be used to analyze the gathered data and create a prediction model.

 (1)

*D. Decision Tree Method*

 In data analysis and predictive modeling, one of the most popular techniques for making decisions is the decision tree process [19]. These decision tree algorithms can be used in a variety of contexts, including business analysis, pattern recognition, and data classification [20]. Also, by using methods like ensemble decision trees, which aggregate several decision trees to increase prediction accuracy, the utility of decision trees may be enhanced [21]. Text recognition [23] and medical image processing [22] are two domains where this technique has been used.

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*E. Implementation of C.45*

 According to by [24] The C4.5 algorithm is described as a method for creating decision trees in its publication. The ID3 algorithm generates a decision by using characteristics, training labels, and training samples as inputs. This algorithm's basic idea is to create a decision tree by determining which attribute, sometimes referred to as the greatest profit value, has the highest gain value based on the attribute's entropy value, which is then used to choose classification attributes. After that, the entropy and gain values are calculated. The formula for calculating gain and entropy is as follows:.

 (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 [25].

 (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*

 In this study, 40 testing and 100 training data sets were used in this study to apply the model. The prediction process is carried out using the Naïve Bayes and Decision Tree algorithms, and the results are obtained through manual calculations. Furthermore, the prediction model for changes in student learning styles after the Covid-19 pandemic is explained using Rapidminer software. Further details about the dataset design can be seen in Table 1 below.

Table 1. Design of Research Dataset

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| 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  |

# 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 [26] 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 [27].

 (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.

 (5)

 (6)

 *A. Evaluating Precision, Recall, and Accuracy on Post-Pandemic Learning Data Labels*

 The precision, recall, and accuracy test results on datasets labeled with post-pandemic learning conditions are shown in this section (refer to Tables 2 and 3). We found that the precision, recall, and accuracy levels varied throughout five tests using various training data (50 to 90 samples). The tests with the greatest accuracy, both at 68.75%, were those with 70 and 90 data samples; in contrast, the accuracy of the other tests varied from 63.41% to 66.67%.

Table 2. Summary of Naïve Bayes Test Results on Post-Pandemic Learning Data-labels

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| No | Total Training Data  | TotalTesting Data | PrecisionNaïve Bayes (%)  | Recall Naïve Bayes (%)  | Accuracy Naïve Bayes (%) |
| 1 | 100 | 50 | 70,59  | 66,67  | 66,67  |
| 2 | 100 | 60 | 65,22 | 75,00  | 64,86  |
| 3 | 100 | 70 | 64,00  | 72,73  | 63,41  |
| 4 | 100 | 80 | 66,67 | 75,00  | 65,91  |
| 5 | 100 | 90 | 66,67 | 84,62 | 68,75  |

 According to test results, the number of data affects how well Naïve Bayes performs. More information could improve recognition. Based on a variety of training and testing data, Table 3 displays the Decision Tree model's performance. 100 training data and 50–90 testing data were utilized in this research..

Table 3. Summary of Decision Tree Test Results on Post-Pandemic Learning Data-labels

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| No | Total Training Data  | TotalTesting Data | PrecisionDecision Tree (%)  | Recall Decision Tree (%)  | Accuracy Decision Tree (%) |
| 1 | 100 | 50 | 80,00  | 88,89  | 81,82  |
| 2 | 100 | 60 | 84,21  | 80,00  | 81,08  |
| 3 | 100 | 70 | 85,71  | 81,82  | 82,89  |
| 4 | 100 | 80 | 84,00  | 87,50  | 84,89  |
| 5 | 100 | 90 | 83,33  | 96,15  | 87,50  |

 The Decision Tree model's precision ranged from 80.00% to 85.71%, demonstrating its capacity to provide positive predictions with accuracy. The recall percentage, which varied from 80.00% to 96.15%, demonstrated the model's ability to accurately identify affirmative cases. The model's capacity to correctly identify cases—both positive and negative—was demonstrated by its accuracy, which ranged from 81.82% to 87.50%. In summary, the Decision Tree model demonstrated great levels of accuracy, recall, and precision.

*B. Analysis of Results*

 Using test data from 80 and 90, Naïve Bayes had the greatest results for post-pandemic learning labels, with precision of 66.67%, recall of 84.62%, and accuracy of 68.75%. This distribution is seen in Graph 1.

Graph 1. Naïve Bayes Distribution for Post-Covid 19 Pandemic Learning Styles

 The Decision Tree approach yielded the greatest results for post-pandemic learning situations, with accuracy of 87.50%, recall of 96.15%, and precision of 83.33% on 90 test data analysis. The Decision Tree method's tree structure with pertinent properties is shown in Figure 4.

Fig.4 Decision Tree Results for Post-Pandemic Condition Labels

 According to Graph 2, which presents a summary of the findings, the Decision Tree technique is the most successful in predicting post-pandemic learning circumstances, with an average accuracy of 88.99%. Therefore, the Decision Tree approach is the recommended technique for post-pandemic forecasts within the scope of this research .

Graph 2. Method Comparison Summary for Post-Covid-19 Pandemic Learning Conditions

# 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 Decision Tree model is clearly superior to the other models in terms of accuracy, recall, and precision, according to the evaluation findings. This model consistently shows high levels of accuracy, ranging from 80.00% to 85.71%, throughout five tests with different quantities of training data. This suggests that it can reliably forecast good outcomes.

 The model's effectiveness in accurately detecting affirmative instances is further indicated by the large recall range, which spans from 80.00% to 96.15%. In the meanwhile, the accuracy of the model ranges from 81.82% to 87.50%, demonstrating its ability to correctly categorize both positive and negative situations. The Decision Tree model demonstrates its efficacy in producing correct predictions throughout the evaluated data with consistently high levels of precision, recall, and accuracy..

*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 [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 [29] 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 [30] 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 [31] 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 [32], 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 [33] 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 [34]. 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 [35].

 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.

# CONCLUSSION

 The results of the research assess the precision, recall, and accuracy of the Decision Tree and Naïve Bayes algorithms in post-pandemic learning scenarios. The Decision Tree demonstrated a continuous high level of precision (80.00% to 85.71%) and varying but effective recall (80.00% to 96.15%), indicating that it was accurate in making predictions and correctly selecting affirmative situations. Its accuracy (81.82% to 87.50%) attests to its capacity to accurately categorize instances in a variety of datasets. This indicates continued efficacy in accurate forecasting.

 Naïve Bayes and Decision Tree integration in systems design demonstrates its effectiveness in identifying pandemic-induced shifts in students' learning preferences. Decision trees help to comprehend changing styles throughout changes in schooling, and Naïve Bayes performs well in online environments.

 This merging offers a comprehensive perspective on how students adjust to remote learning, promoting flexible approaches that may change with the demands of the classroom. The epidemic puts established teaching techniques to the test but also offers chances to utilize technology. Using these techniques promotes individualized instruction and adaptive tactics in the present educational environment by providing a more accurate study of changing learning patterns.

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