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Decision Support System for Identifying Student Learning Styles in Elementary School using Naïve Bayes Algorithm

Ikhsanul Khakim , Ahmad Heru Mujianto, Tanhella Zein Vitadiar, Ginanjar Setyo Permadi

Abstract— ***Identifying student learning styles is essential for teachers to design effective and adaptive teaching strategies. At SDN Rejoagung 3, this process is currently conducted manually through observation and interviews, which are prone to subjective bias. This research develops a web-based decision support system to classify student learning styles—Visual, Auditory, and Kinesthetic—using the Naïve Bayes algorithm. The system was built using data collected via questionnaires from students in grades 1 to 6. Testing was conducted using a confusion matrix to evaluate the model's performance. The results show that the Naïve Bayes algorithm successfully classified learning styles with an accuracy of 94.12%. This system provides a more objective and systematic tool for teachers to identify students' preferences, enabling more personalized instructional delivery in an elementary school context.***

Index Terms— **Educational Data Mining, Gaya Belajar, Naïve Bayes, Website,.**

I. INTRODUCTION

CURRENT advances in information technology demand personalized education through the recognition of students' learning styles, categorized as visual, auditory, or kinesthetic. Understanding these styles is crucial for teachers to align their instructional methods with how students process information. However, at SDN Rejoagung 3, the identification of learning styles is currently conducted manually through traditional observation and interviews. This manual approach is highly prone to subjective bias and often leads to inaccuracies, which in turn results in suboptimal teaching strategies and decreased student engagement.

While several studies have explored learning style classification, there remains a gap in practical, web-based implementations specifically tailored for the elementary school context to support real-time teacher decision-making. Previous research often focuses on algorithmic performance in controlled environments but lacks a streamlined workflow—from digital questionnaire distribution to automated reporting—that can be easily accessed by teachers in a school setting. This research addresses this gap by developing a web-based Decision Support System (DSS) that automates the classification process, providing a more objective and systematic tool for educators.

The primary contribution of this study lies in the implementation of the Naïve Bayes algorithm within a dedicated web platform to identify the learning styles of students in grades 1 to 6. Naïve Bayes was selected for its high computational efficiency and robust performance with categorical data derived from educational questionnaires. By integrating this algorithm into a web interface, this study provides a practical solution to reduce teacher subjectivity, simplify data management, and ultimately support the design of more adaptive and personalized teaching strategies in the classroom.

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II. LITERATURE REVIEW

A. Classification Method

Classification is a fundamental data mining process used to develop models that distinguish and categorize data into specific classes based on distinct attributes (Nasution et al., 2023). By identifying patterns in labeled data, this method enables the prediction of categories for new, unlabeled objects. Implementing machine learning algorithms, classification generates models in forms such as decision trees or logical rules, providing an effective tool for data management and decision support.

B. Learning_Method

Learning styles represent an individual's unique way of absorbing, organizing, and processing information. Understanding these styles is crucial for implementing

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Ikhsanul Khakim is with the Department of Informatics Engineering, Faculty of Information Technology, Universitas Hasyim Asy'ari, Jombang, Indonesia (e-mail: ngunmangun12@gmail.com).

Ahmad Heru Mujianto is with the Department of Informatics Engineering, Faculty of Information Technology, Universitas Hasyim Asy'ari, Jombang, Indonesia (e-mail: ahmadmujianto@unhasy.ac.id).

Tanhella Zein Vitadiar is with the Department of Informatics Engineering, Faculty of Information Technology, Universitas Hasyim Asy'ari, Jombang, Indonesia (e-mail: tanhellavitadiar@unhasy.ac.id).

Chamdan Mashuri is with the Department of Informatics Engineering, Faculty of Information Technology, Universitas Hasyim Asy'ari, Jombang, Indonesia (corresponding author, e-mail: chamdanmashuri@unhasy.ac.id).

differentiated learning and enhancing academic achievement. At SD Negeri Rejoagung 3, the absence of a systematic identification tool necessitates the development of an information system. Previous research using the Naïve Bayes method in RapidMiner has demonstrated an 80% accuracy rate in classifying these styles.

Generally, learning styles are categorized into three primary types: Visual (learning through seeing), Auditory (learning through hearing and discussion), and Kinesthetic (learning through movement and physical touch). While individuals may possess a combination of these abilities, one typically dominates. Identifying this dominant style is essential for teachers to design optimal instructional strategies tailored to each student's potential. There are three learning styles: visual, auditory and kinesthetic.

Visual learning is a style where sight plays a crucial role in receiving and processing information. This type emphasizes visual acuity, meaning students require concrete evidence or visualizations, such as images, diagrams, and demonstrations, to understand material effectively (Supit, 2023). Recommended teaching approaches include using graphics, films, slides, and serial picture cards. Key characteristics of visual learners include Closely observing the speaker's lips or movements, Preferring demonstrations over oral instructions, Using body gestures or visual cues when communicating, Having difficulty remembering purely verbal information, Remaining focused even in noisy environments.

Auditory learners rely on hearing as their primary tool for receiving and remembering information. These individuals often find it easier to understand material by listening rather than reading, and they may struggle with writing tasks. According to Supit (2023), common traits include talking to oneself, moving lips while reading, and preferring to spell out loud. Recommended learning approaches involve using voice recorders, engaging in verbal discussions, and summarizing material orally to test comprehension. Key characteristics of auditory learners include: Excellent ability to remember group discussions, Skillful at recognizing and mimicking music or sounds, A tendency to be talkative and a preference for listening over reading, Difficulty focusing on visual information like bulletin boards.

Kinesthetic learning involves processing information through physical movement, touch, and direct action (Rahmawati, 2021). This style emphasizes hands-on activities and object manipulation. Kinesthetic individuals often need to physically engage with the subject matter to remember it effectively. Recommended approaches include using props, laboratory practice, and educational games, with frequent short breaks during the learning process. Key characteristics of kinesthetic learners include: A strong desire to touch everything and a difficulty sitting still, Good physical coordination and a preference for active hands-on tasks, A requirement for real objects as learning aids, Difficulty understanding abstract concepts such as symbols or maps.

C. Data Mining

Data mining is the process of extracting valuable information and hidden patterns from large databases to build models for knowledge discovery. It has become a popular tool due to its accessibility, even for those without deep programming knowledge. In the academic field, the application of data mining to solve specific educational problems is known as Educational Data Mining (EDM). EDM focuses on exploring unique data, such as student logs and test results, to improve teaching processes and learning outcomes (Sumarlin, 2025).

Data mining serves two primary functions: the Descriptive Function, which identifies hidden patterns and data characteristics, and the Predictive Function, which uses known variables to forecast unknown values. The process follows several structured stages:

- Data Cleaning: Removing errors or inconsistent information.
- Data Integration: Combining multiple data sources.
- Data Selection: Retrieving relevant data for analysis.
- Data Transformation: Converting data into optimal formats for processing.
- Mining Process: Applying algorithms, such as Naïve Bayes, to extract key information.
- Pattern Evaluation: Identifying valuable patterns to form a knowledge base.
- Knowledge Presentation: Visualizing the results for end-users.

D. Naïve Bayes

Naïve Bayes is a fundamental classification algorithm in data mining based on probability and statistics derived from Bayes' Theorem (Munir, 2023). This method predicts future outcomes by calculating probabilities based on prior experiences or historical data (Lase et al., 2024). The algorithm is characterized by its "Naïve" assumption, which treats all attributes as independent, meaning the presence of a specific feature in a class is unrelated to any other feature (Halfiani & Wibowo, 2022). This assumption makes the algorithm highly efficient and easy to implement for complex datasets. The mathematical formula for the Naïve Bayes algorithm is as follows:

$$P(H|X) = \frac{P(X|H).P(H)}{P(X)}$$

Where:

X : Data with an unknown class

H : Hypothesis that data X is a specific class

P(H|X) : Probability of hypothesis H based on X condition

P(H) : Probability of hypothesis H (Prior Probability)

P(X|H) : Probability of X based on condition H

P(X) : Prior probability that evidence of X occurs without any other hypotheses

E. Related Works and Research Gap

Several studies have implemented machine learning algorithms to identify student learning styles. Salsabila (2023) achieved a high accuracy of 98.85% using the Naïve Bayes method at SMPIT Al-Anwar, demonstrating the algorithm's effectiveness in a junior high school environment. Another study by Suherman et al. (2024) developed a web-based classification system using the C4.5 algorithm at Universitas Serang Raya (UNSERA), which reached an accuracy of 95%. While these studies show superior accuracy, they focus on older students (middle school and university levels) whose cognitive consistency in answering questionnaires may differ from younger children.

Additionally, Setiawan et al. (2025) applied Naïve Bayes to 7th-grade students at SMP Negeri 1 Kandat, reporting an accuracy of 86.76%. This study highlighted the potential of machine learning for classroom intervention but remained focused on the junior high school level. Despite the existence of these high-performing models, there is a distinct lack of research specifically addressing the elementary school context, where teachers face unique challenges in objectively identifying learning styles due to the students' developmental stages.

The novelty of this research lies in its application within the elementary school level (SD Negeri Rejoagung 3). While previous works reached higher accuracy in older demographics, this study proves that Naïve Bayes is highly reliable for primary education, achieving an accuracy of 94.12%. This research fills the gap by providing a systematic tool for elementary teachers to reduce subjective bias in young learners' assessments, enabling earlier and more accurate personalized learning interventions.

The comparison of these studies is summarized in Table 1.

Table 1. A. Related Works and Research Gap

Researcher (Year)	Algorithm	Research Context (Level)	Accuracy
Salsabila (2023)	Naïve Bayes	Junior High School (SMPIT)	98.85%
Suherman et al. (2024)	C4.5	University (UNSERA)	95.00%
Setiawan et al. (2025)	Naïve Bayes	Junior High School (SMP)	86.76%
This Study (2025)	**Naïve Bayes**	**Elementary School (SD)**	**94.12%**

III. RESEARCH METHODOLOGY

A. Research Method

This research aims to design and develop a web-based application to classify student learning styles (Visual, Auditory, and Kinesthetic) at SD Negeri Rejoagung 3. The study addresses the need for an objective and systematic identification tool to replace biased manual observations. By implementing the Naïve Bayes algorithm, known for its effectiveness in probability-based data mining, the system processes data from student questionnaires. The application's performance is validated using Black Box Testing for functionality and Confusion Matrix for accuracy. Ultimately, this system serves as a decision support tool for teachers to facilitate personalized teaching methods and optimize student academic achievement.

The research procedure consists of several systematic stages: problem identification, literature study, data collection, requirements analysis, method analysis, system design, and implementation. The workflow and details for each stage are as follows:

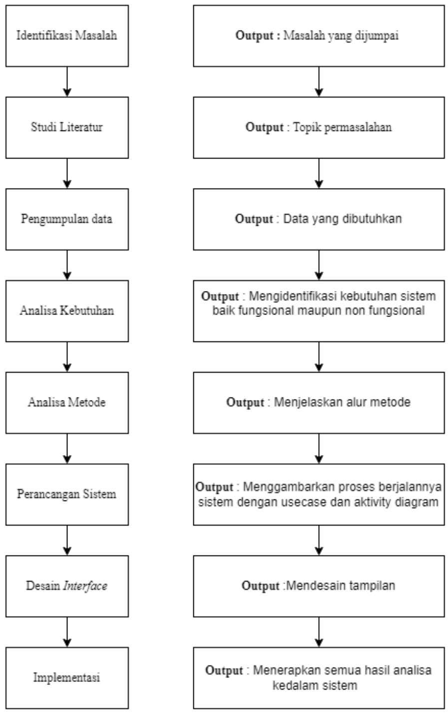

Fig. 1. Research Method

B. Data Collection Techniques

(1) Primary Data

Primary data is obtained directly from the first source through questionnaires filled out by students at SD Negeri Rejoagung 3. This questionnaire is designed to collect raw data regarding each student's preferences and learning style characteristics. The data will be divided into two sets: training data and testing data, which will serve as the main data for classification. The dataset for this research was obtained from SD Negeri Rejoagung 3.

The data collection process involved students from Grade 1 to Grade 6 to ensure a comprehensive representation of elementary level learning styles. A total of 102 students participated as respondents. The data was divided into two sets: 85 students from Grades 2 to 6 served as the training data, while 17 students from Grade 1 were used as the testing data.

The primary instrument used was a closed-ended questionnaire consisting of 21 items adapted from the Visual, Auditory, and Kinesthetic (VAK) model. To ensure the instrument's quality, a validity and reliability test was conducted. The reliability test yielded a Cronbach's Alpha coefficient of 0.783, which is greater than the threshold of 0.60, indicating that the questionnaire items are reliable and consistent for measuring student learning styles. Each respondent's original label (ground truth) was determined based on the highest score achieved among the three categories in the validated questionnaire, which was then confirmed by the classroom teacher's observations.

(2) Secondary Data
Secondary data is gathered from relevant written sources. This includes material from literature studies used as the theoretical foundation to understand the concepts of learning styles and the Naïve Bayes algorithm. These sources also serve as the primary basis for developing relevant questionnaire instruments.

C. Analysis Method

The primary method used in this research is the Naïve Bayes algorithm, a highly effective classification approach in data mining based on the probability principles of Bayes' Theorem. This method predicts future class probabilities based on observed historical data. The defining characteristic of Naïve Bayes is its "naïve" assumption that all attributes in the dataset are independent of each other. Despite this simplicity, the algorithm remains popular and efficient, especially for high-dimensional data, due to its ease of implementation, speed, and tolerance to irrelevant attributes.

Technically, this method works by calculating the posterior probability for each class based on the observed features and selecting the class with the highest probability as the prediction. The mathematical model for calculating the posterior probability is:

$$P(C_k|x_1,x_2,\ldots,x_n) = \frac{P(C_k) \times (x_1|C_k) \times P(x_2|C_k) \times \ldots \times P(x_n|C_k)}{P(x_1) \times P(x_2) \times \ldots \times P(x_n)}$$

Description:

$P(Ck|\, x1,..xn)$: The posterior probability of class given the features .

$P(Ck)$: The prior probability of class before observing the data.

$P(x1|\, Ck)$: The conditional probability of feature occurring within class .

$x1,.., xn$: The observed features or attributes.

D. System Workflow Design

System Flowchart The system begins with a mandatory login for users or admins. Once authenticated, the system displays the main Dashboard. Users then select a student to fill out the questionnaire. After completion, the system proceeds to the Accuracy Test Data page. If the user chooses to proceed with validation, the system executes back-end calculations using the Naïve Bayes method and displays the detailed accuracy results.

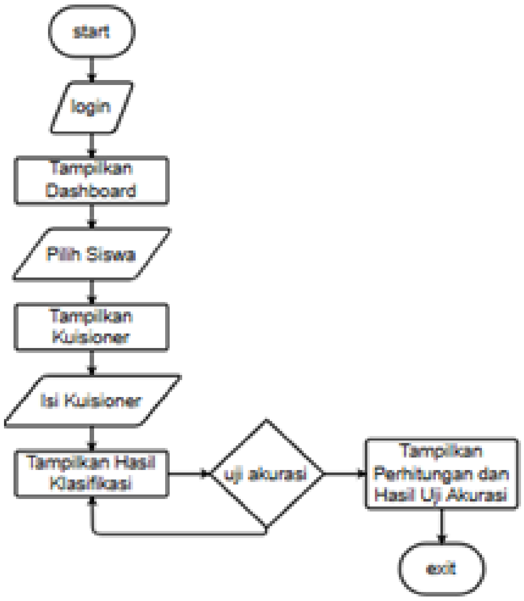

Fig. 2. System Flowchart

User Design Flowchart In the initial stage, Users (Parents/Guardians) can access the website without logging in. The system displays the learning style classification results for all students on the Dashboard. This data is derived from the classification menu, which is updated by the Admin after testing each student.

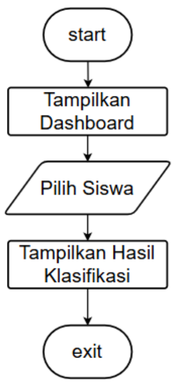

Fig. 3. User Design Flowchart

Admin Design Flowchart Admins must undergo an authentication process by entering a username and password. Upon successful login, the Admin gains full access to the Dashboard, the system's control center. Admins hold essential rights to manage operational data, including student records, training data for the Naïve Bayes model, questionnaire management, and accuracy validation reports.

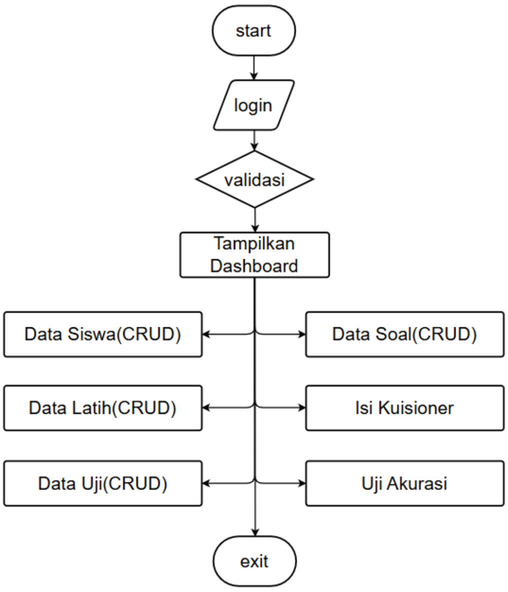

Fig. 4. Admin Design Flowchart

IV. RESULTS AND DISCUSSION

The research successfully developed a web-based Student Learning Style Classification Application, serving as a Decision Support System for teachers at SD Negeri Rejoagung. Built using PHP Native and operated via the XAMPP web server, the system objectively classifies learning styles by processing questionnaire data. For testing purposes, data from students in grades 2 through 6 were utilized as the training set, while data from grade 1 students served as the testing set to validate the model's performance. The final interface provides accurate predictions of each student's dominant learning style (Visual, Auditory, or Kinesthetic) assisting teachers in tailoring their instructional methods. The following section displays the system's user interface.

A. Home Interface

Fig. 6. Home Interface

Upon accessing the system, users are immediately directed to the home page, which serves as the primary entry point for both Admins and non-Admins. This page displays the percentage of student learning styles stored in the system, derived from both training and testing datasets. The training data consists of original classification results from students in grades 2 to 6. Meanwhile, the testing data is utilized to validate the Naïve Bayes classification performance on grade 1 students, generating predicted class outcomes. The interface of the home page is shown below.

B. Students

The student data menu displays comprehensive records of all students from grades 1 to 6 involved in this study. As indicated by the previous charts, this dataset combines both training and testing data from SD Negeri Rejoagung 3. The available information includes student names, gender, total responses for each category, and their dominant learning style. Additionally, a graphical representation is provided to illustrate the specific learning style composition for each individual student. The interface is shown in the image below.

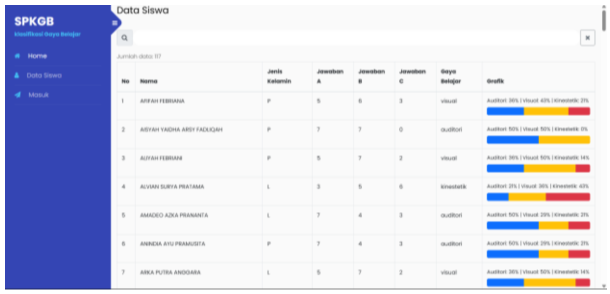

Fig. 5. Students Interface

C. Login

The next section discusses the login page. While users initially access the home page, further access to the system's management features requires authentication. Users must log in to the system to gain advanced administrative or operational privileges. After logging into the system, users are granted expanded privileges to manage data. This enhanced access is reflected in the sidebar, which displays several additional administrative menus, including training data, testing data, and questionnaire management, The interface for the login page is presented below

Fig. 7. Interface

D. Training

One of the available menus is the training data page, which allows users to upload Excel files containing training datasets into the database or delete them. In a Naïve Bayes classification study, training data is essential as it serves as the foundation for the classification process. Users can upload multiple training data files to this page as needed. The interface for the training data page is shown in the image below:

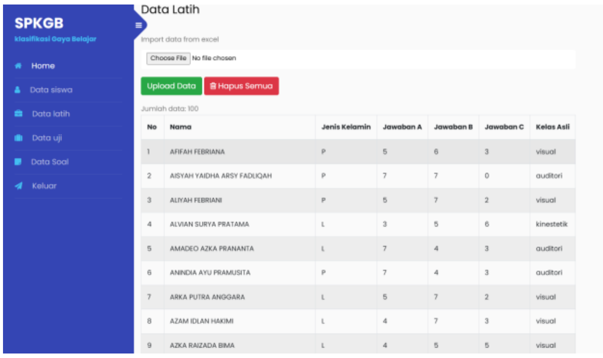

Fig. 8. Interface

E. Testing

In addition to training data, the testing data page is a critical component of this research. As shown in the interface, users can upload or delete datasets that are to be tested. Furthermore, this page features an additional menu to execute the classification process using the Naïve Bayes method. When the process is initiated, the system displays a pop-up showing the detailed calculations for each test case Subsequently, the system presents the calculation results along with the accuracy level, comparing the original classes against the predicted results. The interface of the testing data page is shown in the image below:

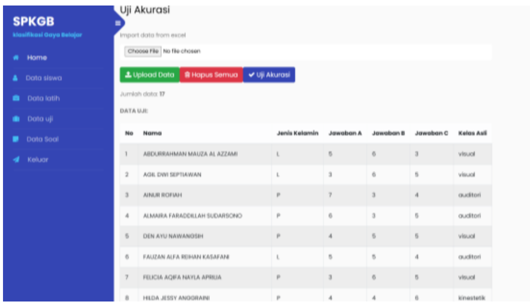

Fig. 9. Interface

The evaluation results using a confusion matrix with 17 test samples showed that the system achieved an accuracy of **94.12%**. Detailed analysis reveals that the system correctly classified all students in the Auditory and Kinesthetic categories. However, one student with a Visual learning style was incorrectly predicted as Kinesthetic. This minor error indicates a slight overlap in questionnaire response patterns between the two styles among elementary students, yet the overall performance remains highly reliable for educational decision support.

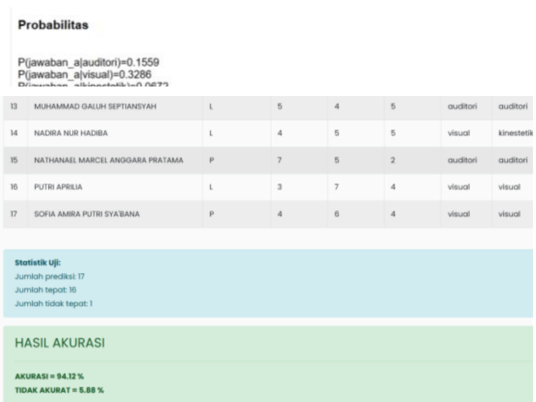

Fig. 11. Interface

Table 2. Confussion Matrix multi class

Actual \ Predicted	V	A	K	Total Actual
Visual	**9**	0	1	10
Auditory	0	**5**	0	5
Kinesthetic	0	0	**2**	2
Total Predicted	9	5	3	**17**

The calculation of the system's accuracy is as follows:

$$A = \frac{\sum TP}{Total\ Samples} x100\%$$

$$A = \frac{9+5+2}{17} x100\% = \frac{16}{17} x100\%$$

$$A = 94{,}12\%$$

The high accuracy rate of 94.12% indicates that the Naïve Bayes algorithm is highly effective for identifying learning styles in the elementary school context. The single error observed suggests a slight overlap in characteristics between visual and auditory traits in the questionnaire responses of young learners. However, for practical use in a Decision Support System, this level of performance provides a reliable basis for teachers to tailor their instructional methods.

F. Question

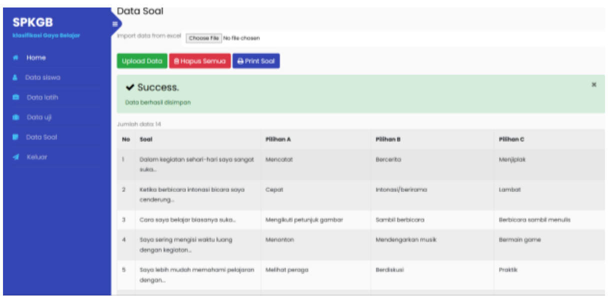

Fig. 12. Interface

The final page of the system is the questionnaire data page. While this page is not directly involved in the classification process, it assists users in the data collection phase. Similar to previous pages, users can upload questionnaire data into the system, with the option to delete and re-upload if the data is incorrect. Once the data is finalized, users can print it directly from the system to generate ready-to-use questionnaire sheets for the research subjects.

V. Conclusion

This research has successfully designed and developed a web-based Student Learning Style Classification Application using PHP Native and the XAMPP web server. The application serves as an effective Decision Support System, offering an objective solution to the challenges of identifying learning styles at SD Negeri Rejoagung 3, which were previously prone to subjective bias through manual observation. The system efficiently manages student data, processes questionnaire inputs, and provides accurate learning style predictions (Visual, Auditory, or Kinesthetic).

The Naïve Bayes algorithm proved highly effective for this case study. Model evaluation results show that the algorithm achieved a superior accuracy rate of 94.12%. This high level of accuracy confirms that Naïve Bayes is a reliable and appropriate method for processing categorical data from learning style questionnaires. Furthermore, the implementation of Log-Probability techniques in the final calculations successfully prevented numerical underflow, ensuring the validity of the classification results.

Overall, this study contributes to improving human resource quality and optimizing student potential. The measurable and accurate predictions enable teachers to personalize their teaching strategies and methods. By precisely identifying each student's dominant learning preference, teachers can design more adaptive instructional materials, ultimately leading to enhanced comprehension, increased motivation, and better academic achievement for students at SD Negeri Rejoagung 3.

VI. Suggestions

For the sustainability and development of this learning style classification system, it is recommended that SD Negeri Rejoagung 3 actively integrate these accurate prediction results (94.12%) into the preparation of Lesson Plans (RPP) to implement more personalized learning through differentiated instruction. For future researchers, it is suggested to explore other classification methods, such as Support Vector Machine (SVM) or Deep Learning, to compare and test whether the accuracy can be further improved. Additionally, developing a mobile-based version of the application would enhance accessibility for teachers, and including specific teaching material recommendations (e.g., video links for Visual learners) based on the classification results would add significant value to the system.

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