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Classification of Book Borrowing Interests Based on Class and Reading Category at the Mi Village Library of Tenggerejo using Naive Bayes

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Abstract

School libraries play an essential role in supporting students' literacy development. However, the low borrowing rate at MI Desa Tenggerejo indicates a mismatch between available collections and students' reading interests. This study aimed to develop a classification system for book borrowing interest based on grade level and reading categories using the Naïve Bayes algorithm. The dataset included student information, reading categories, and borrowing history. The research process consisted of requirement analysis, system design, implementation, and model evaluation. Input variables included students' grade level, reading categories, and book return punctuality, while the output variable was the borrowing interest level (High, Medium, Low). The implementation results showed that the system was successfully developed and could classify students' borrowing interests according to actual data. The evaluation achieved an accuracy of 53.57%, with the highest misclassification occurring between the Medium and High categories. This indicated that although the system functioned as designed, the classification performance required further improvement through feature enrichment, balanced training data, and the application of alternative or ensemble algorithms. This study is expected to serve as a foundation for schools to design data-driven strategies to enhance literacy in primary education.

Keywords: *Borrowing Interest, Library, Naïve Bayes, Classification, Literacy*

1. Introduction

Education plays a central role in shaping the character, competence, and competitiveness of the nation's future generations. In the era of globalization, marked by rapid technological advancement and the swift flow of information, the quality of human resources is determined not only by mastery of knowledge but also by the ability to manage information critically, reflectively, and productively. Therefore, the development of the education sector must focus on strengthening literacy as a key pillar for creating adaptive and visionary learners.

Literacy is no longer merely defined as the ability to read and write, but has evolved into a skill to understand, evaluate, and use information effectively. [1] states that literacy also includes critical thinking, filtering relevant information, and applying it in real life. Unfortunately, although literacy has become a strategic issue, Indonesia's reading interest remains concerning. According to UNESCO data cited by [1], Indonesia ranks 60th out of 61 countries in terms of reading interest, indicating that literacy challenges remain significant.

This condition calls for breakthroughs from educational institutions, particularly in optimizing the roles of teachers, librarians, and school administrators. At the elementary school level, a literacy culture must be cultivated early through a supportive learning environment, one of which is the school library. However, in practice, school libraries are still underutilized. A study by [2] found that student visits to libraries are often seasonal, occurring mainly when there are school assignments. Furthermore, book collections frequently do not match students' needs and interests, hindering the development of a sustainable reading culture.

A similar situation exists in MI Desa Tenggerejo. Although the school has a relatively diverse collection, the low borrowing rate indicates a mismatch between available reading materials and students' preferences. This gap is exacerbated by the absence of a data-driven analytical system capable of mapping students' reading interests. The lack of information technology utilization in library management makes it difficult for schools to make strategic, evidence-based decisions.

Moreover, each grade level has different psychological characteristics and reading preferences. Lower-grade students tend to prefer picture books or light stories, while upper-grade students seek more complex reading materials. Therefore, a generic approach can no longer be used in managing collections. A system is needed to classify reading interests based on grade level and reading category so that book collections and learning approaches can be tailored to individual needs. Teachers play a vital role in guiding students' literacy development. If students' reading interest data can be recorded digitally, teachers can integrate the classification results into more effective and contextual teaching strategies. This concept aligns with *data-driven learning*, an approach increasingly applied in modern education [3].

Advancements in information technology provide great opportunities to design data-based decision-support systems. In the context of school libraries, technology can be used to build a reading interest classification system based on students' borrowing history. By applying *data mining* techniques, schools can analyze borrowing patterns, group students according to reading preferences, and develop more accurate and evidence-based literacy enhancement strategies.

One relevant *data mining* method for this classification task is the Naïve Bayes algorithm, known for its efficiency and effectiveness in handling categorical data such as book categories and student grade levels. Despite assuming feature independence, the algorithm has proven reliable in many educational studies. [4] showed that Naïve Bayes could classify library users' reading interests with up to 65% accuracy, while [5] reported an accuracy of 98.74% in predicting students at risk of dropping out using the same algorithm. These findings indicate that Naïve Bayes is a feasible method for data-based educational classification. Furthermore, Naïve Bayes has also been applied as a machine learning technique to identify healthcare workers' mental health conditions during the COVID-19 pandemic, assuming that analyzed features are independent of one another, consistent with the algorithm's foundational principle [6].

However, at MI Islamiyah Jatenan, there is still no structured evaluation system to assess students' reading preferences. Currently, book borrowing occurs without data analysis that could reveal students' tendencies based on grade level and reading category. As a result, teachers, librarians, and school operators lack a solid foundation for designing targeted literacy programs. Book collections are typically arranged based on intuition or habit rather than actual student needs. The absence of a digital classification system makes decision-making speculative and not data-driven. Teachers lack references to adapt teaching materials to students' interests, librarians struggle to curate appealing collections, and school operators are unable to generate systematic reports or procurement strategies. Yet, technology holds significant potential to address these limitations.

In this context, a reading interest classification system based on the Naïve Bayes algorithm is needed to analyze students' borrowing history and categorize them according to relevant reading preferences. This system will serve as a foundation for schools to develop smarter, adaptive, and contextual literacy strategies.

Based on these considerations, this study aims to develop a reading interest classification system using the Naïve Bayes algorithm for the library of MI Desa Tenggerejo. The system will analyze borrowing data and map students' reading preferences based on grade level and book category. Three main user roles will be involved teachers, librarians, and school operators each with complementary responsibilities. Teachers can use classification results to adjust teaching strategies, librarians can curate more suitable collections, and school operators can manage data and generate reports.

This system functions not only as a technical tool but also as an instrument of change in library management. Through a data-driven digital approach, schools can design literacy strategies that are more responsive to students' evolving interests and needs. In the future, this system can be further developed into a personalized and interactive reading recommendation platform, transforming the library into a dynamic center of literacy. Overall, implementing this reading interest classification system is expected to make a positive contribution to improving literacy management effectiveness in elementary schools, especially in resource-limited areas with a strong commitment to strengthening literacy.

2. Methodology

The stages of this research were systematically structured to produce a reading interest classification system that can be directly applied to library management at Madrasah Ibtidaiyah (MI) Desa Tenggerejo. This study falls under the category of applied research, as its outcome is a system that can be utilized by librarians and teachers to classify students' book borrowing interests based on historical data. The research employed a quantitative approach, focusing on the processing of measurable numerical data that can be objectively analyzed and statistically validated.

The primary data analyzed consisted of students' book borrowing records, which were processed using a data mining method with the Naïve Bayes classification algorithm, a technique within machine learning that operates on the principle of conditional probability. The attributes used in the classification process included student grade level, reading category, and book return status, all of which represent students' reading behavior patterns. Through this approach, the study aimed to identify patterns of reading interest among students and to evaluate the performance of the classification model based on its achieved accuracy level.

Furthermore, the use of the Naïve Bayes algorithm is supported by previous research, such as study [7] which demonstrated the algorithm's effectiveness in analyzing borrowing data and producing accurate classifications of reading interests. Therefore, the research stages were designed not only to develop a technical system but also to implement a data-driven analytical framework that supports decision-making for improving literacy culture in elementary school environments.

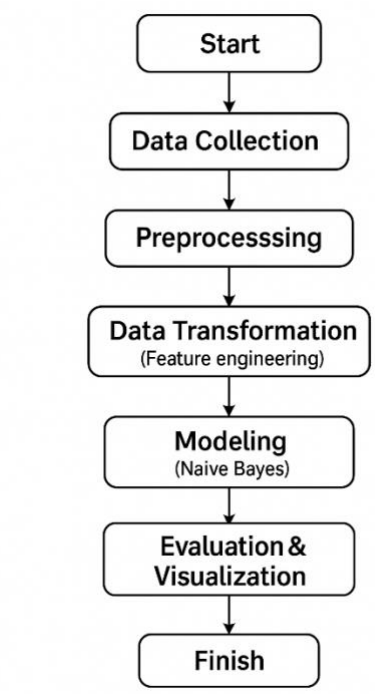

Fig. 1: Research Stages

Figure 1 illustrates the research stages, beginning with data collection, which involves gathering relevant data required for the study. The next step is preprocessing, aimed at cleaning and preparing the data to ensure its quality and consistency before use. This is followed by data transformation (feature engineering), where essential features are constructed to support the analytical process. The modeling stage is then carried out using the Naïve Bayes algorithm to build a classification or prediction model based on the processed data. Subsequently, the model undergoes evaluation and visualization to assess its performance and to present the results in an informative and interpretable manner. Finally, the research concludes with result interpretation and formulation of recommendations for further development and future research directions.

3. Results and Discussion

In this research, system requirements analysis covers the elements necessary to build a system. These requirements include data collection from observations, formula use, system design, and the system implementation process.

3.1. Observation Data

The data observation stage is a crucial first step in this study, as it determines the quality and representativeness of the data used for analysis. The research data were obtained directly from the library information system of MI Desa Tenggerejo, which had been previously implemented to support literacy activities within the school. The dataset consists of four main types: book data, student data, visit data, and borrowing data.

The book data include a total of 951 titles, categorized based on the Dewey Decimal Classification (DDC) system into nine main categories: General Works, Philosophy, Religion, Social Sciences, Language, Fiction, Arts/Sports/Entertainment, Literature, and Biography/Earth Science/History. This categorization allows the system to identify correlations between reading types and students' interest levels in particular categories.

The student data, comprising 140 entries from two schools MI Islamiyah and MI Infarul Ghoy contain details such as full name, student identification number, class level, and other basic demographic information. Additionally, the visit data record 1,300 entries, providing insights into the frequency of students' interactions with the library and serving as an indicator of their literacy engagement. The borrowing data, totaling 491 entries, form the core of the study and include information on book titles, borrowing dates, target and actual return dates, and the number of late-return days. These four datasets were then integrated to produce the main dataset used in the reading interest classification process.

3.2. Data Collection Results

After obtaining the raw data, the next step involved data preprocessing to ensure that all data were consistent in format and values. This stage included data cleaning, normalization, duplicate removal (deduplication), date format standardization, and handling of missing values.

For instance, the borrowing dataset contained inconsistent date formats between the "Borrow Date" and "Return Date" columns. Through normalization, the date formats were standardized into the YYYY-MM-DD format to facilitate system processing. Additionally, the book return delay values, initially recorded as text, were converted into numerical values so they could serve as input variables during the classification stage.

The cleaned data were then combined with a standard word dictionary dataset, which acted as a reference for text normalization. This dictionary was used to convert nonstandard words into their standard forms following the Indonesian Language Spelling Guidelines

(PUEBI). For example, “pavorit” was corrected to “favorit,” “lu” to “kamu,” and “bang” to “abang.” This step was crucial to prevent the system from interpreting different spellings of the same word as separate entities during the classification process, thereby improving the consistency and accuracy of text-based data analysis.

Table 1: Example of Borrowing Data After Preprocessing

No	Full_Name	School	Book_Title	Borrow_Date	Return_Date (Target)	Actual_Return_Date	Late (Days)
487	dwi candra kusuma	mi islamiyah	atlas propinsi kalimantan timur	kamis, 27-06-2024 114014	minggu, 30-06-2024	selasa, 09-07-2024 081112	9
488	dwi candra kusuma	mi islamiyah	matematika dalam sains	kamis, 13-04-2023 142145	minggu, 16-04-2023	kamis, 20-04-2023 081502	4
489	dwi candra kusuma	mi islamiyah	beternak ikan koi	kamis, 13-04-2023 100035	minggu, 16-04-2023	senin, 24-04-2023 085823	8
490	dwi candra kusuma	mi islamiyah	budi pekerti kepada guru	rabu, 21-02-2024 153041	sabtu, 24-02-2024	rabu, 28-02-2024 122352	4
491	dwi candra kusuma	mi islamiyah	uks	sabtu, 25-11-2023 124103	selasa, 28-11-2023	rabu, 06-12-2023 144059	8

The final result of this stage produces a clean, uniform dataset, ready to be used in the data transformation and classification process using the Naive Bayes algorithm.

3.3. Application of the Naïve Bayes Method

At this stage, the Naïve Bayes algorithm was applied to predict students’ book borrowing interest at the MI Desa Tenggerejo Library based on several main variables: student grade level, book category, and timeliness of book returns. The selection of this method was grounded in its simplicity and effectiveness in handling categorical data with relatively large datasets.

The main stages in applying the Naïve Bayes method are as follows:

1. Prior Probability Calculation , determining the initial probability for each reading interest class (High, Medium, and Low) based on the proportion of data in the training set.
2. Likelihood Calculation, measuring the probability of occurrence for each feature (such as book category or return status) within a specific class.
3. Laplace Smoothing Application, addressing the zero probability problem that arises when certain combinations of features and classes do not appear in the training data.
4. Posterior Probability Calculation, multiplying the prior and likelihood values and normalizing the result so that the total probability equals one.
5. Final Prediction, selecting the class with the highest posterior probability as the predicted result for each student’s record.

The system’s core function, naive_bayes(), returns a set of probability values representing each reading interest class (prob_high, prob_medium, and prob_low) and assigns the final label based on the highest probability.

From the calculation results, the highest combined probability value appeared in the “Medium” category, meaning the system predicted that the student’s borrowing interest was at a medium level. This finding aligns with the empirical characteristics of the dataset, where the majority of students demonstrated a moderate level of reading interest.

3.4. Classification Results and Model Evaluation

The classification results showed that, out of 140 students analyzed, 74 students (53%) fell into the Medium Interest category, 30 students (21%) were categorized as High Interest, and 36 students (26%) were classified as Low Interest. This distribution indicates that most students display a fair level of reading interest, though not yet reaching a highly enthusiastic level.

To assess model performance, an evaluation using a confusion matrix was conducted, comparing the system’s predicted outputs with the actual labels. The evaluation yielded an accuracy rate of 53.57%, indicating that more than half of the system’s predictions matched the true reading interest classifications of the students.

Table 2: Model Evaluation Accuracy Results

Model	Accuracy (%)
Naïve Bayes	**53,6**
Gradient Boosting	50,0
Ensemble Voting	35,7
Random Forest	17,9

As shown in Table 2, the Naïve Bayes algorithm outperformed the other three models tested using Google Colab with the Scikit-learn library. Although the overall accuracy remains modest, the Naïve Bayes model demonstrated the most stable and reliable performance for the dataset used in this study. This suggests that the model is well-suited as a baseline for classification of reading interest, especially when dealing with small or moderately sized educational datasets.

Table 3. Confusion Matrix

Actual / Predicted	Tinggi	Sedang	Rendah
Tinggi	7	0	2
Sedang	20	2	8
Rendah	1	2	6

3.5. Evaluation Analysis

The classification results presented in Table 3 show that the model achieved an accuracy rate of 53.57%, indicating that it still struggles to correctly identify certain categories particularly the “Medium Interest” class, which is often misclassified as either High or Low. Several factors contributed to this limitation:

1. Unbalanced Data Distribution
   The number of records in the “Medium” class is significantly higher than in the “High” and “Low” classes. This imbalance caused the model to become biased toward the majority class, reducing its ability to correctly classify samples from minority categories.
2. Limited Features
   The features used in this study were limited to borrowing data, return timeliness, and book category. Other influential variables such as library visit frequency, reading duration, or students’ personal reading preferences were not included, though they could substantially improve model performance.
3. Independence Assumption in Naïve Bayes
   The Naïve Bayes algorithm assumes that features are independent of one another. However, in real-world conditions, variables such as borrowing frequency and return punctuality are often correlated. This dependency leads to inaccurate probability estimations and, consequently, misclassifications.
4. Quality of Training Data
   The relatively small dataset size and presence of noisy data for example, when students borrow books for assignments rather than personal interest make it difficult for the model to fully capture genuine reading patterns.

Overall, while the Naïve Bayes classifier provides a good baseline model, its performance can be improved by applying data balancing techniques, adding more representative features, and refining data preprocessing steps. These improvements are expected to yield higher accuracy and more reliable classification results in future research.

3.6. System Design

A. Context Diagram

A context diagram illustrates a single large process that represents the overall system as a whole. It is the highest level of a Data Flow Diagram (DFD) and consists of only one main process that encapsulates the system’s general functionality and its interactions with external entities [8]. In this study, the context diagram of the book borrowing interest classification system at MI Desa Tenggerejo demonstrates how all users librarians, school operators, and teachers interact with the system [9].

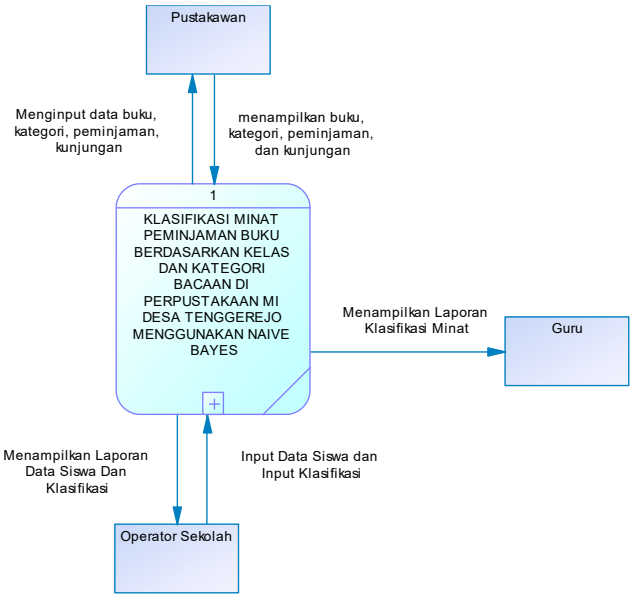

Fig. 2: Context Diagram

As shown in Figure 2, the system processes focus on managing data and classifying students’ reading interests based on their grade level and reading category using the Naïve Bayes algorithm. The external entities include the librarian, responsible for inputting and viewing data on books, categories, borrowings, and visits; the school operator, responsible for managing student data and classification results; and the teacher, who serves as the recipient of classification reports. The diagram clearly represents the main process and data flow between users and the system in a structured and integrated manner.

B. Data Flow Diagram Level 1

A DFD Level 1 diagram elaborates the system's main process into several interconnected subprocesses, showing how data flow occurs between users, the system, and data storage components (data stores). In a leveled DFD, each lower level provides a more detailed representation of the processes at the higher level. The DFD development process usually begins from the context diagram (Level 0) and then breaks down into DFD Level 1 and beyond [10].

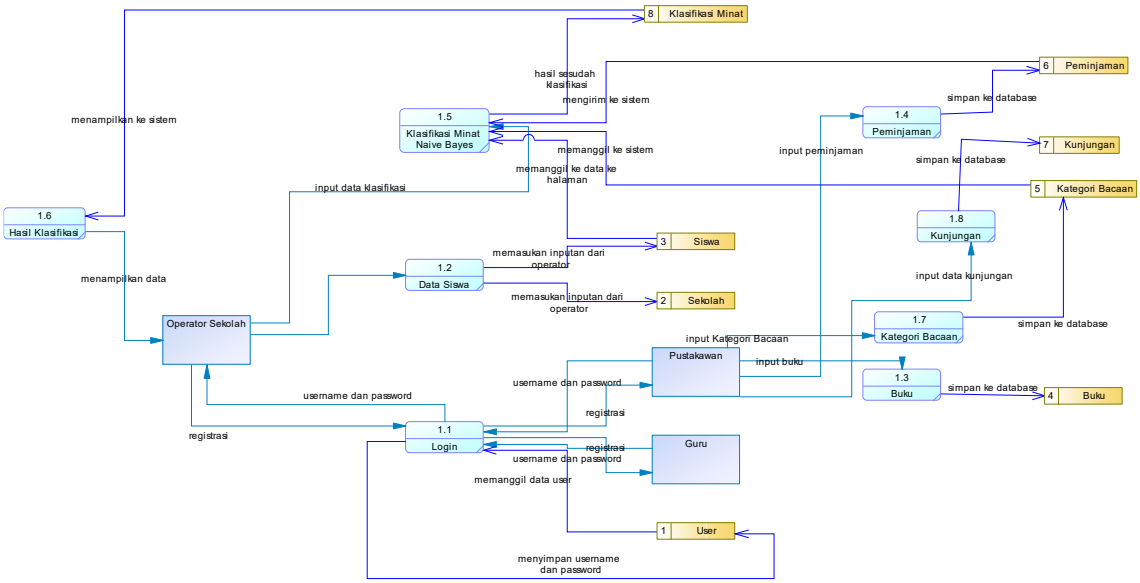

Fig. 3: Data Flow Diagram Level 1

Figure 3 illustrates how the book borrowing interest classification system at MI Desa Tenggerejo is structured into several key processes: Login, Student Data Management, Book and Reading Category Data, Borrowing Data, Visit Data, and the Interest Classification Process using the Naïve Bayes algorithm. The system begins when users librarians, school operators, or teachers log in to access features based on their roles. The school operator manages student data, while the librarian oversees book data, reading categories, borrowings, and visits. Once the data are entered, the system performs a classification process linking student data with borrowing records, generating predictions of reading interest levels. These results are stored in the database and can be viewed as reports by the operator or teacher.

The external entities include librarians, school operators, and teachers, who directly engage in data input, verification, and report review. Additionally, students and schools act as primary data sources for reading interest identification. Several data stores are also involved in the system: Student Data, School Data, Book Data, Reading Category Data, Borrowing Data, Visit Data, and Classification Results. The DFD Level 1 thus provides a clear and detailed view of the data flow, process relationships, and the interaction between system components that support the analysis of students' reading interests.

C. Physical Data Model

The Physical Data Model (PDM) represents the real implementation of the Logical Data Model within the database used by the system, with SQL Server serving as the database management platform [11]

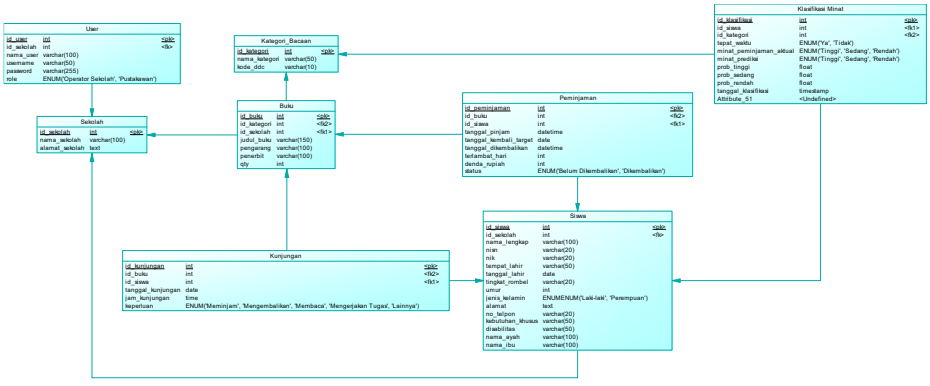

Fig. 4: Physical Data Model

As illustrated in Figure 4, the PDM describes the main structure of the database for the book borrowing interest classification system, consisting of several key entities:

1. User, which stores information about system users such as school operators and librarians, including attributes like username, password, and access level.
2. School, which records school information and maintains a direct relationship with the Student entity containing personal student data.

3. Reading_Category, which includes book types such as fiction, non-fiction, and religion.
4. Book, which stores book-related data including title, category, and location.
5. Borrowing, which logs book borrowing transactions and return statuses.
6. Visit, which records library visit activities, including time, purpose, and descriptions.
7. Classification_Min, which serves as the core table, storing reading interest classification results both actual data and predictions generated by the Naïve Bayes algorithm, along with their corresponding probability values.

All of these entities are interconnected and collectively form the foundational database structure for the MySQL-based application used in the book borrowing interest classification system. This model ensures that the system can manage, store, and process data efficiently while maintaining the integrity and consistency required for accurate classification results.

3.7. Implementasi Sistem

A. Login Page

The initial display of the system shows the login interface, which serves as the main entry point for users, as illustrated in Figure 5 below.

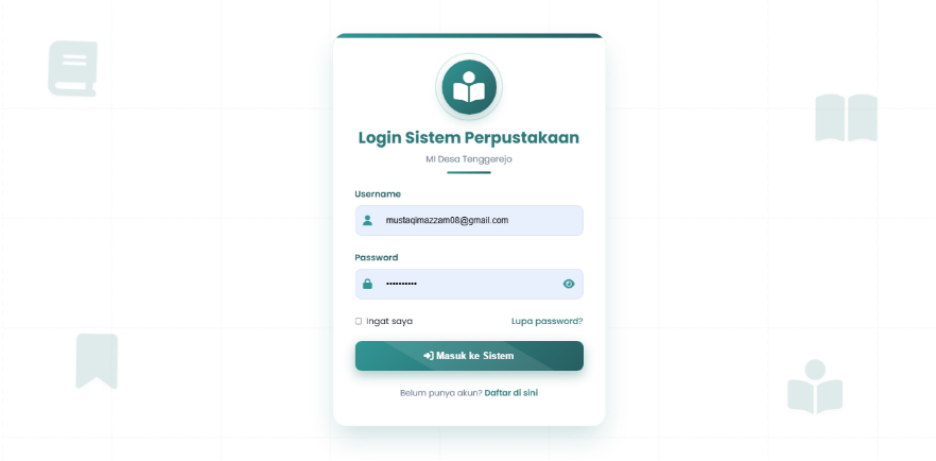

Fig. 5: Login Page

The login page in Figure 5 consists of two main components: a user authentication form and an access verification mechanism. Through this page, each user is required to enter their username and password according to their respective roles. Once validated, the system redirects the user to the main interface based on their access level whether as a librarian, operator, or teacher. This feature ensures data security and prevents unauthorized access to sensitive information, such as student classification results.

B. Student Data Page

As shown in Figure 6 below, this page is used to manage student data, including *name, student ID (NISN), gender,* and *class*. This data serves as one of the main inputs in the student reading interest classification process.

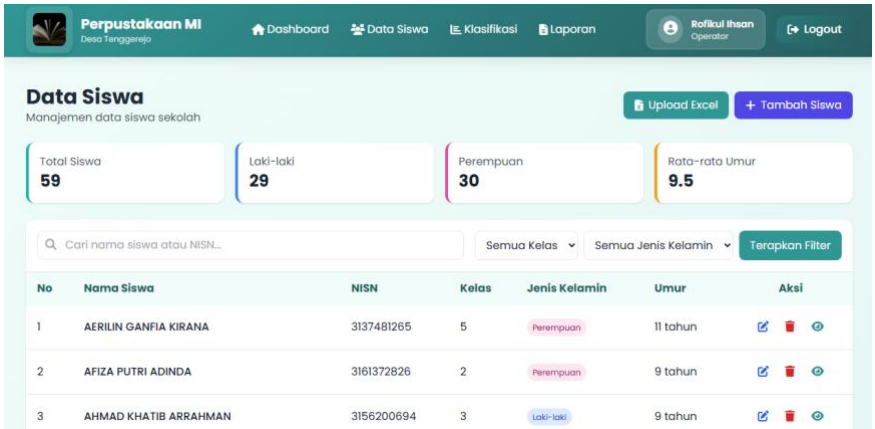

Fig. 6: Student Data Management Page

This page is designed for **school operators**, who are responsible for inputting and updating student information. Its core features include adding new students, editing existing records, deleting data, and searching students by name or class. The stored data consist of attributes such as full name, NISN, gender, class, and school, which are linked to the **School** entity in the database. This data plays a critical role in classification, particularly in identifying reading patterns based on class level or age group. Moreover, the page provides an **export function** to allow operators to back up or transfer data to other systems when needed.

C. Book Borrowing Page

As shown in Figure 7 below, this page is used to record all book borrowing activities by students, which form the basis for analyzing reading interests.

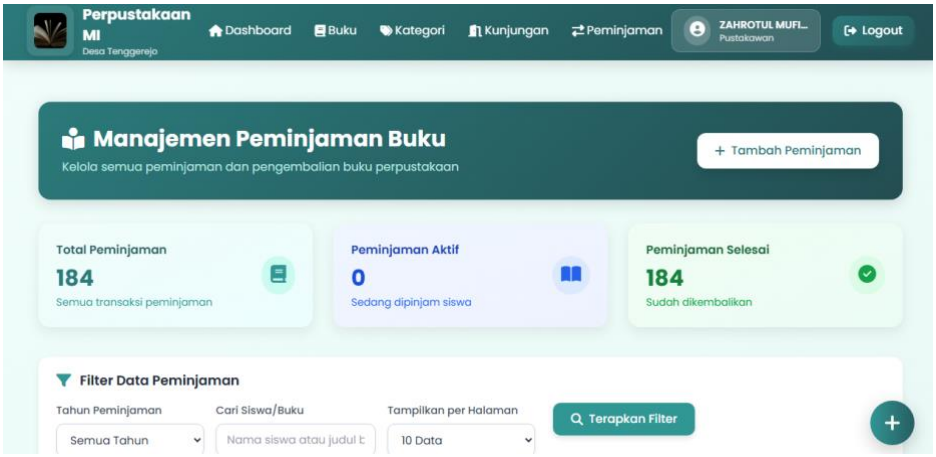

Fig. 7: Book Borrowing Page

On this page, librarians can add new transactions whenever a student borrows or returns a book. Each record includes details such as student name, book title, borrowing date, return date, delay duration, and book status (borrowed or returned). This data is one of the most crucial features of the system, as it forms the foundation for the Naïve Bayes algorithm to identify the relationship between reading categories and borrowing frequency. The system automatically stores all borrowing records in the database, which are later processed during the classification stage. Additionally, librarians can filter data based on book category or borrowing period to monitor students' literacy activity trends over time.

D. Reading Interest Classification Page

As shown in Figure 8 below, this page is the core component of the system, displaying the results of the reading interest analysis obtained through the Naïve Bayes algorithm.

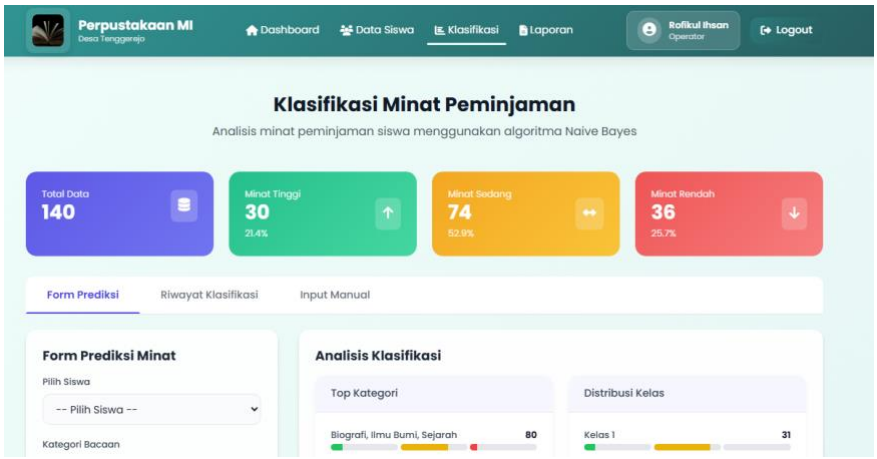

Fig. 8: Reading Interest Classification Page

This page integrates data from student, borrowing, and reading category tables. The system displays predicted results labeled into three categories: High Interest, Medium Interest, and Low Interest. Each result also includes the probability value of each class, representing the model's confidence in its prediction. The interface is designed to allow librarians or operators to easily view reading patterns visually. A distribution chart at the bottom of the page shows the comparison of students across interest levels. This feature helps schools identify students who may require additional encouragement or literacy guidance.

E. Classification Report Page

As shown in Figure 9 below, this page presents the final classification results in a tabulated report format, serving as an evaluation tool for literacy activities.

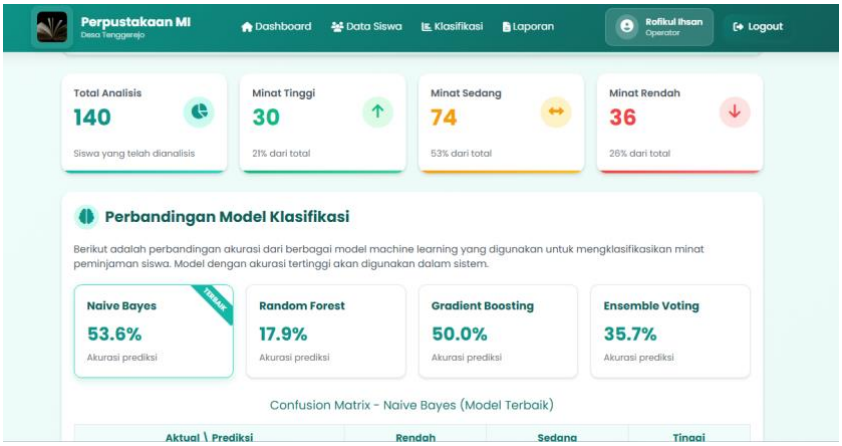

Fig. 9: Classification Report Page

This page is designed so that teachers and school operators can easily interpret the model's analytical results. The system displays a list of students along with their reading interest levels, frequently borrowed book categories, and most recent classification outcomes. The report can be downloaded in Excel format or printed directly as an official document for literacy program evaluation. This feature provides actionable feedback for literacy program implementation, enabling the school to identify student reading trends, determine the most popular reading categories, and develop targeted strategies to enhance literacy based on the classification results.

4. Conclusion

Based on the research that has been conducted, it can be concluded that the student reading interest classification system at MI Desa Tenggerejo was successfully designed and implemented using the Naïve Bayes algorithm, utilizing data on book borrowings, student records, and library visits. The system is equipped with role-based access control for teachers, operators, and librarians, allowing each user to perform their respective functions effectively according to their responsibilities. The classification results were able to group students' reading interests into three categories High, Medium, and Low based on reading categories following the Dewey Decimal Classification (DDC) scheme, thereby providing insight into reading patterns both at the individual and class levels.

Although the system functioned according to its design, evaluation results indicated an accuracy level of 53.57%, with the highest misclassification occurring between the Medium and High interest categories. This relatively low accuracy was primarily caused by imbalanced training data and limited feature representation. Therefore, future research is recommended to expand the dataset, incorporate additional relevant attributes, and optimize the preprocessing stage to achieve higher accuracy and produce more representative classification outcomes.

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