Digital Zone
Jurnal Teknologi Informasi dan Komunikasi
Vol: 15 No 01 2024 **E-ISSN: 2477-3255**
Accepted by the Editor: 31-03-2024 | Revision: 09-05-2024 | Published: 31-05-2024

Recommendation System to Determine Achievement Students Using Naïve Bayes and Simple Additive Weighting (SAW) Methods

Ahmad Jazaudhi'fi1, Anik Vega Vitianingsih2*, Yudi Kristyawan3, Anastasia Lidya Maukar4, Verdi Yasin5
1,2,3Informatics Department, Universitas Dr. Soetomo, Surabaya, Indonesia
4Industrial Engineering Department, President University, Bekasi, Indonesia
5 Informatics Department, Sekolah Tinggi Manajemen Informatika dan komputer Jayakarta,
e-mail: jazaudhifiahmad@gmail.com 2vega@unitomo.ac.id* , 3yudi@unitomo.ac.id, 4almaukar@president.ac.id, 5verdiyasin29@gmail.com

Abstract

Giving appreciation to outstanding students can motivate students to compete with each other in learning. MA Tanwirul Qulub Tanggungan often experiences difficulties in determining outstanding students due to There is no application that can assist school management in identifying outstanding students, the implementation is considered less than optimal. besides that, the determination of outstanding students is still based on report cards that are only ranked, and there are no criteria that refer to the K-13 curriculum. The purpose of this research is to offer a solution to create a recommendation system for selecting outstanding students using the parameters of midterm exams, final exams, assignments, attendance, attitude, extracurricular activities, organizations, and award certificates using decision support system techniques. Extracurricular grades are taken from Scouting activities only because students are generally required to participate in them. Naïve Bayes and Simple Additive Weighting methods are used in this research, where the Naïve Bayes method classifies the categories of outstanding students and not, while the SAW method is used for ranking. The contribution of this research has the potential to increase school efficiency in student assessment and support efforts to improve the quality of education by rewarding students appropriately. The validation test results of Naïve Bayes and SAW techniques get an accuracy value of 100%, which shows that the SAW method can produce the best alternative recommendations.

Keywords: *Recommendation System, Decision Support System, Outstanding Students, Naïve Bayes, Simple Additive Weighting*

1. Introduction

Technological innovation is needed in management and decision-making for educational institutions [1]. This aligns with the expert opinion that education has experienced a very rapid development, characterized by the development of digital learning, where education is usually still carried out conventionally [2]. Outstanding students have a crucial role in the progress of a nation. Selecting outstanding students is expected to produce the next generation of competent nations so that they can continue to lead the country [3]. This research is very important for educational institutions in Indonesia, as it helps to increase the effectiveness in objectively assessing student achievement. The innovative approach of combining Naive Bayes and Simple Additive Weighting methods enables schools to provide more appropriate rewards and support to outstanding students. Thus, educational institutions can encourage students' learning motivation, identify individual needs, and improve the overall quality of education.

Identification of outstanding students for an educational institution is essential every year. *MA Tanwirul Qulub Tanggungan* is a school in the Bojonegoro district. The school consistently organizes the selection of outstanding students every year. In the process of identifying student achievement, the problem faced by schools is that they often experience difficulties in determining student achievement objectively and efficiently at school, because no application can assist school management in identifying student achievement. In addition, the determination of outstanding students is still based on report cards that are only ranked, and there are no criteria that refer to the K-13 curriculum involving several criteria that must be taken because there are three domains of competence that are assessed, namely attitude competence, knowledge competence, and skill competence [4], so that in its implementation it is still considered less than optimal and the lack of a clear framework in weighing various factors of student achievement is also a factor causing these difficulties. As a result, there is uncertainty in identifying outstanding students and giving appropriate awards, which in turn can affect the quality of assessment and decision-making in schools. Similar research has been done, such as the Intelligent System for Predicting Learning Achievement Using the Naïve Bayes Algorithm at *MA Sains Roudlotul Qur'an Lamongan* [5]. The Topsis method supports decision systems for selecting outstanding students [6]. In both studies, the determination of student achievement is only within the scope of the lesson without involving non-academics to be considered. Thus, a decision support system (DSS) is needed to assess outstanding students, which can assist in determining exceptional students so that they are correct on target.

Some previous studies related to SPK in determining student achievement include the Analytical Hierarchy Process Method and Order of Preference Based on the TOPSIS Technique Assist Student Selection Decision Support System [7]. The study used the criteria of attendance, tardiness, cognitive scores, moral values, and achievement with AHP and TOPSIS methods. Furthermore, research conducted at SMP Information and Technology Surakarta uses the NN (nearest neighbor) and Simple Additive Weighting method based on the parameters of report card scores, written tests, income, and achievements [8]. Then, the Implementation of the K-Means Clustering Algorithm for Selection of Outstanding Students Based on Activeness in the Learning Process [9], the Web-Based Profile Matching Method Utilizing the Decision Support System to Select Outstanding Students [10], and the implementation of K-Means and K-Nearest Neighbors in the Outstanding Student Category [11]. The review's findings indicate that no study has been conducted utilizing the Naive Bayes and simple additive weighting (SAW) methodologies to examine the characteristics of midterm exams, final exams, assignments, attendance, attitude, extracurricular activities, organizations, and reward certificates. This research will focus on a decision support system in determining student achievement each year.

Based on the background of the problem, the purpose of this research is to develop a decision support system to determine outstanding students using the Naive Bayes and Simple Additive Weighting (SAW) methods. Previous research did not combine the two methods to analyze the relationship between variables and model the determination of outstanding students. Analyzing the relationship between variables can help improve prediction accuracy in determining outstanding students. The Naïve Bayes method is used to determine the probability of an outstanding or non-achieving student category because of its ability to classify a variable using probability and statistical methods [12]. While the Simple Additive Weighting method is used to calculate the weight of student criteria because of its ability to make more precise assessments, based on the value of the criteria and the weight of the required level of

https://doi.org/10.31849/digitalzone.v15i1.19746

importance [13]. The results of this study are expected to contribute to improving the quality of education and increasing student learning motivation. By having the right decision support system, schools or educational institutions can make more objective and effective decisions in determining outstanding students.

2. Research Methods

There are several processes in making a recommendation system to determine student achievement. The flowchart is a diagram that describes the algorithm, workflow, or active system process [13]. The recommendation system process algorithm for determining outstanding students with The Naive Bayes (NB) technique is applied to categorize the types of outstanding and non-outstanding student categories[14]. In contrast, the SAW method performs ranking to find superior students [15]. Algorithm image in Figure 1.

Based on Figure 1 above, the calculation process of the Naïve Bayes method has several stages. Explained the initial process after logging in by taking training data from student data consisting of the input process of criteria and criteria values, sub-criteria values, followed by inputting for testing data. After the input, calculating the prior probability of each class using the Naïve Bayes method begins with calculating the posterior probability and then multiplying all probability values until getting the results of the information for testing data with outstanding status and not. After doing the Naïve Bayes process, it is continued by calculating the SAW method, and there are brief stages for calculating the SAW method. To generate a decision matrix, after normalizing the matrix, multiply the normalized matrix by the outcomes of the subsequent matrix operation., the final process until the system displays the top rank of the recommendation for determining outstanding students.

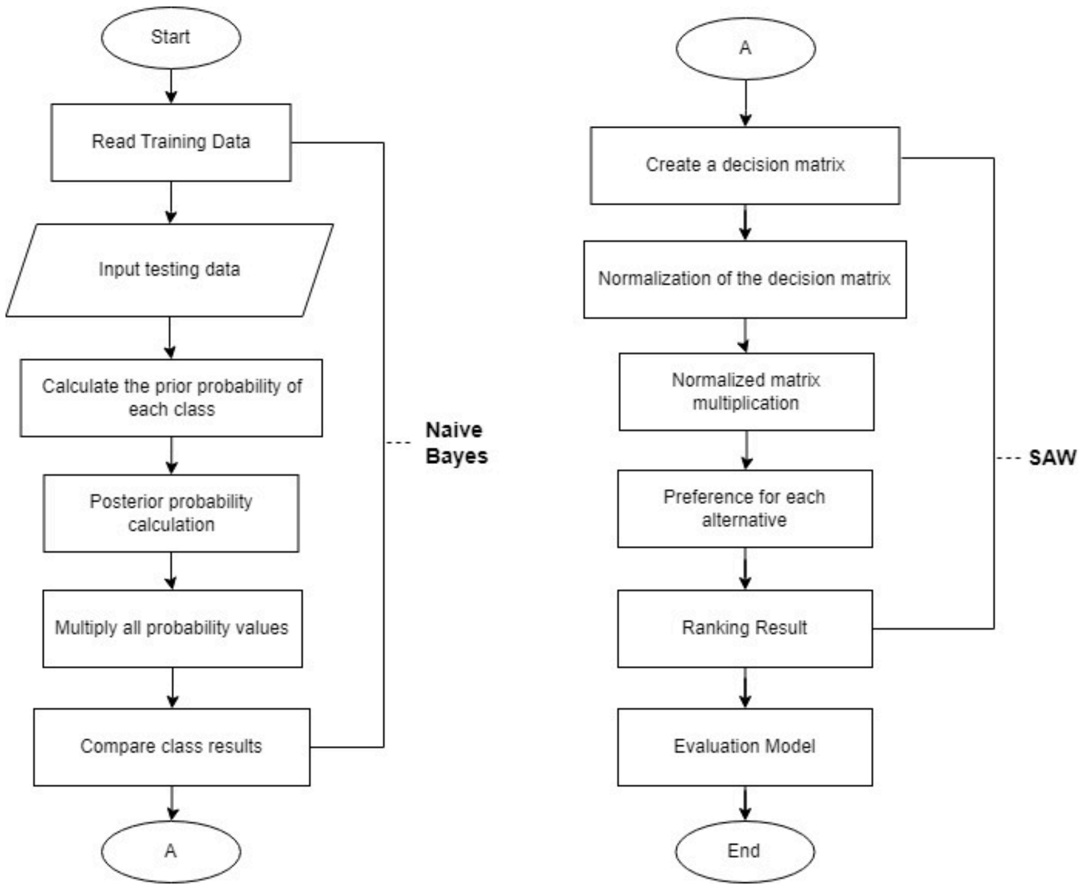

Figure 1. Flow of the Recommendation System for Student Achievement

Step 1: Criteria data used as parameters in recommending outstanding students in Table 1.

Table 1 Outstanding Students Parameter

Code	Criteria
C1	Midterm Exams
C2	Final Exams
C3	Assignment Grade
C4	Attendance
C5	Attitude
C6	Extracurricular Value
C7	Organization
C8	Award Charter

Step 2: Alternative data used for determining recommendations for outstanding students using 5 *MA Tanwirul Qulub Tanggungan* student data in Table 2.

Table 2 Alternative for Outstanding Students

Code	Alternative
A1	Learner1
A2	Learner2
A3	Learner3
A4	Learner4
A5	Learner5

Step 3: Converting attribute values to categories in Table 3.

Table 3. Categorial Criteria

Criteria	Weighted	Categorical	Value
Midterm and Final Exams Assignments	91 – 100	Very Good	4
	81 – 90	Good	3
	70 – 80	Fair	2
	< 70	Less	1
Attendance	100%	Very Good	4
	80% – 90%	Good	3
	70% – 79%	Fair	2
	< 70%	Less	1
Attitude, Extracurricular	A	Very Good	4
	B	Good	3
	C	Fair	2
	D	Less	1
Organization & Award Charter	Available	Good	2
	No	Less	1

2.1. Metode Naïve Bayes

Naïve Bayes is the most popular classifier method used with good accuracy[16]. Due to its simplicity, This method is frequently applied in machine learning [17]. According to its ability to classify a variable using probability and statistical methods, the Naïve Bayes method will be very fitting in classifying outstanding students. This is because the Naïve Bayes method can classify data quickly and accurately, even with a small amount of training data[18]. The Naïve Bayes method process[19].

https://doi.org/10.31849/digitalzone.v15i1.19746

Step 1: Calculation of the probability value of each class (Prior Probability) using Equation (1). Where $P(Ci)$ is label probability on *Ci*, $\sum ci$ is the amount of data with the class label *Ci*, and n is the total number of training data.

$$P(Ci) = \frac{\sum ci}{n} \quad (1)$$

Step 2: Calculation of the probability value of each feature (Posterior Probability) using Equation (2). Where $P(Xi|Ci)$ is the probability of feature *xi* with a label in class *Ci*, $\sum xi|ci$ is the number of data of feature xi with a label in class *Ci*, and $\sum ci$ is the number of data with a label in class *Ci.*

$$P(Xi|Ci) = \frac{\sum xi|ci}{\sum ci} \quad (2)$$

Step 3: Multiplication probability values in each class or multiply rating values between attributes using Equation (3). If the probability of class Ci in a known X is $P\left(\frac{Xi}{C1}\right)$, $\sum xi|ci$ is a probability on class label *Ci*, and $\sum ci$ is the probability rate of feature Xi with class label Ci.

$$P\,(Ci) \prod_{i=1}^{n} P\left(\frac{Xi}{C1}\right) = P\left(\frac{Ci}{X}\right) \quad (3)$$

Step 4: Comparing class results

2.2. Metode Simple Additive Weighting (SAW)

The total of the performance ranking weights for each option in relation to each criterion is calculated using a straightforward additive weighting technique. Computational procedures are needed to process a scale on which the choice matrix (X) may be compared to all other ranks [20]. Phases of the Simple Additive Weighting computation process [21]:
Step 1: Ensuring the parameters to be used Ci, before the decision-making step
Step 2: Double-check or assess the suitability of each option against each parameter
Step 3: Finish the decision matrix process based on the parameter Ci ,The equation is used to normalize the matrix according to the type of attribute, for example the benefit attribute or the cost attribute, resulting in a normalized matrix R.
Step 4: The ranking process produces the final result in the total of multiplying the weight vector by the normalized matrix R to get the greatest value chosen as the best answer (Ai). The SAW method's fourth equation for matrix normalization.

$$r_{ij} = \begin{cases} \dfrac{x_{ij}}{\underset{i}{Max}\, x_{ij}} \\ \dfrac{\underset{i}{Min}\, x_{ij}}{x_{ij}} \end{cases} \quad (4)$$

justification The preference score for each option (V_i) is established as given in Equation (5), and the value of (V_i) shows that alternative Ai has stronger preference. In relation to attribute r_ij is the normalized ability assessment of $j = 1,2, \ldots, n$ and $i = 1,2, \ldots . m$ compose the substitute Cj.

$$V_i = \sum_{j=1}^{n} w_j\, r_{ij} \quad (5)$$

3. Results and Discussion

In this research, we used 228 cleaned student data to classify student achievement the Naive Bayes (NB) technique. Then, The data in this study is divided into two groups: 228 training data and five testing data. This data division aims to determine the data used for training and testing.

Training data is data that already has a class and is used as raw material to train or run the function of an algorithm[22]. Table 4 shows the training data for this study.

Table 4. Training Data of Outstanding Students

No	Midterm Exams	Final Exams	Assignment	Attendance	Attitude	EXTRA	Organization	AWARD	Classification
1	Good	Fair	Less	Very good	Very good	Good	Good	Good	Achievement
2	Fair	Very good	Very good	Very good	Very good	Fair	Good	Good	Achievement
3	Less	Fair	Fair	Fair	Fair	Less	Good	Good	No
4	Fair	Less	Less	Less	Less	Fair	Less	Less	No
…	…	…	…	…	…	…	…	…	…
227	Very good	Very good	Good	Fair	Less	Excellent	Good	Good	Achievement
228	Less	Less	Fair	Good	Very good	Fair	Good	Good	No

The 228 training data shows that the 'No Achievement' class (C0) consists of 102 students, and the 'Achievement' class (C1) comprises 126 students. This calculation uses Equation (1).

$\boxed{P(C0) = \frac{102}{228} = 0{,}447}$; $\boxed{P(C1) = \frac{126}{228} = 0{,}552}$

3.1. Classification of Outstanding Students Using the Naïve Bayes Method

Calculation of posterior probability of students with achievement. Conducted on training data, as much as 228 data were collected using eight criteria variables to calculate each criterion's probability, as demonstrated by Table 5.

Table 5. Exam Score Probability

Criteria	Categories	Count of Categories		Probability	
		Achievement	No	Achievement	No
Midterm Exams Value	Very good	53	7	0,420	0,068
	Good	54	6	0,428	0,058
	Fair	12	48	0,095	0,470
	Less	7	41	0,055	0,401
Final Exams Value	Very good	36	0	0,285	0
	Good	48	24	0,380	0,235
	Fair	24	36	0,190	0,352
	Less	18	42	0,142	0,411
Assignment Grade	Very good	36	12	0,285	0,117
	Good	42	6	0,333	0,058
	Fair	24	48	0,190	0,470
	Less	24	36	0,190	0,352
Attendance Score	Very good	48	12	0,380	0,117
	Good	36	12	0,285	0,117
	Fair	12	24	0,095	0,235
	Less	30	54	0,238	0,529
Attitude Score	Very good	66	30	0,523	0,294
	Good	36	12	0,285	0,117
	Fair	12	36	0,095	0,352

https://doi.org/10.31849/digitalzone.v15i1.19746

Criteria	Categories	Count of Categories		Probability	
		Achievement	No	Achievement	No
	Less	12	24	0,095	0,235
Extracurricular Value	Very good	34	23	0,269	0,225
	Good	33	24	0,261	0,235
	Fair	30	27	0,238	0,264
	Less	29	28	0,230	0,274
Organization Value	Very good	85	67	0,674	0,658
	Less	41	35	0,325	0,343
Award Charter Value	Very good	43	33	0,341	0,323
	Less	83	69	0,658	0,676

Test data, or testing data, is a measurement instrument for evaluating algorithms [23] and is utilized as a starting point for further study. Table 6 displays the testing data used in this investigation.

Table 6. Testing Data of Achievement Students

Midterm Exams	**Final Exams**	**Assignment**	**Attendance**	**Attitude**	**Extra**	**Organization**	**Award**	**Classification**
Good	Very good	Good	Fair	Good	Very good	Good	Less	?

To calculate the classification into the Not Achieving (C0) and Achieving (C1) classes, use Equation (3).

$$P\left(\frac{X}{No\ Achievement}\right) = P\left(\frac{X}{C0}\right)$$

$$P\left(\frac{X}{C0}\right) = (0{,}058 * 0 * 0{,}058 * 0{,}235 * 0{,}117 * 0{,}225 * 0{,}658 * 0{,}676)$$

$$= (0)$$

$$P\left(\frac{C0}{X}\right) = P\left(\frac{X}{C0}\right) * P(C0)$$

$$= (0 * 0{,}447)$$

$$= (0)$$

$$P\left(\frac{X}{Achievement}\right) = P\left(\frac{X}{C1}\right)$$

$$P\left(\frac{X}{C0}\right) = (0{,}428 * 0{,}285 * 0{,}333 * 0{,}095 * 0{,}285 * 0{,}269 * 0{,}674 * 0{,}658)$$

$$= (0{,}000131)$$

$$P\left(\frac{C1}{X}\right) = P\left(\frac{X}{C1}\right) * P(C1)$$

$$= (0{,}000131 * 0{,}552)$$

$$= (0{,}0000723)$$

From the above calculations, it can be concluded that $P(C1|X) > P(C0|X)$, then the testing data is classified into the Achievement class. The results for five testing data are in Table 7.

Table 7. Testing Data Results

No	**Midterm Exams**	**Final Exams**	**Assignment**	**Attendance**	**Attitude**	**Extra**	**Organization**	**Award**	**Classification**

No	Midterm Exams	Final Exams	Assignment	Attendance	Attitude	Extra	Organization	Award	Classification
(A1)	Good	Very good	Good	Fair	Good	Very good	Good	Less	Achievement
(A2)	Fair	Fair	Fair	Less	Very good	Very good	Less	Less	No
(A3)	Good	Good	Fair	Good	Good	Fair	Good	Good	Achievement
(A4)	Less	Fair	Fair	Fair	Fair	Very good	Less	Good	No
(A5)	Fair	Less	Fair	Good	Fair	Good	Good	Less	No

3.2. Ranking Using Simple Additive Weighting Method

To make parameter calculation easier, the types of criteria and their weights are defined. The criteria type determines whether the criteria are included in the "cost" or "benefit". Cost is the smaller the value, the greater, while the benefit is the greater the value, the greater.

Table 8. Criteria and Criteria Weight

Code	Criteria	Attribute	Value
C1	Midterm Exams	Benefit	0,20
C2	Final Exams	Benefit	0,20
C3	Assignment Grade	Benefit	0,10
C4	Attendance	Benefit	0,15
C5	Attitude	Benefit	0,10
C6	Extracurricular Value	Benefit	0,10
C7	Organization	Benefit	0,05
C8	Award Charter	Benefit	0,10

Table 8 shows the determination of criteria values based on how important each criterion is. Criteria with a high level of urgency will get a greater weight because if the calculation is carried out, the weight of these criteria can dominate so that the results obtained follow predictions. The smaller the level of urgency of the criteria, the smaller the weight given. In using the Naïve Bayes Algorithm, what needs to be done is determining the training input and testing target that you want to produce. After determining the criteria and the size of the weights, the next step in calculating The value is found using the Simple Additive Weighting approach of the match level of the criteria with the initial data value. Table 9 determines the suitability rating, and sorting is the stage of determining criteria and weights. It is necessary to make an initial data suitability rating for each criterion.

Table 9. Initial Data Match Rating

No	Midterm Exams	Final Exams	Assignment	Attendance	Attitude	Extra	Organization	Award
A1	Good	Very good	Good	Fair	Good	Very good	Good	Less
A2	Fair	Fair	Fair	Less	Very good	Very good	Less	Less
A3	Good	Good	Fair	Good	Good	Fair	Good	Good

No	Midterm Exams	Final Exams	Assignment	Attendance	Attitude	Extra	Organization	Award
A4	Less	Fair	Fair	Fair	Fair	Very good	Less	Good
A5	Fair	Less	Fair	Good	Fair	Good	Good	Less

For more clarity, As shown in Table 10, each alternative must be evaluated to fulfill each criterion.

Table 10. Alternative Data Suitability Rating

Alternatives	Criteria							
	C1	C2	C3	C4	C5	C6	C7	C8
A1	3	4	3	2	3	4	2	1
A2	2	2	2	1	4	4	1	1
A3	3	3	2	3	3	2	2	2
A4	1	2	2	2	2	4	1	2
A5	2	1	2	3	2	3	2	1

The decision matrix generated from the alternative data suitability rating table is shown in Table 11, and then a decision matrix is made.

Table 11. Decision Matrix

Decision Matrix								
A1	3	4	3	2	3	4	2	1
A2	2	2	2	1	4	4	1	1
A3	3	3	2	3	3	2	2	2
A4	1	2	2	2	2	4	1	2
A5	2	1	2	3	2	3	2	1

Table 12 shows the results of normalizing the decision matrix's alternative value.

Table 12. Matrix Normalization Results

Normalization result								
A1	1	1	1	0,6	0,7	1	1	0,5
A2	0,6	0,5	0,6	0,5	1	1	0,5	2
A3	1	0,7	0,6	1	0,7	0,5	1	1
A4	1	0,5	0,6	0,6	0,5	1	0,5	1
A5	0,6	0,2	0,6	1	0,5	0,7	1	0,5

In calculating this preference, the weight value is multiplied by the value of the R matrix. Weight Value W = [0.20, 0.20, 0.10, 0.15, 0.10, 0.10, 0.05, 0.10] with ranking results in Table 13.

V1 A1 = (0.20x1)+(0.20x1)+(0.10x1)+(0.15x0.6)+(0.10x0.7)+(0.10x1)+(0.05x1)+
(0.10 x0.5) = 1,76

V2 A2 = (0.20x0.6)+(0.20x0.5)+(0.10x0.6)+(0.15x0.5)+(0.10x1)+(0.10x1)+(0.05x0.5)+
(0.10 x2) = 0,78

V3 A3 = (0.20x1)+(0.20x0.7)+(0.10x0.6)+(0.15x1)+(0.10x0.7)+(0.10x0.5)+(0.05x1)+

(0.10x1) = 0,77

V4 A4 = (0.20x1)+(0.20x0.5)+(0.10x0.6)+(0.15x0.6)+(0.10x0.5)+(0.10x1)+(0.05x0.5)+ (0.10 x1) = 0,72

V5 A5 = (0.20x0.6)+(0.20x0.2)+(0.10x0.6)+(0.15x1)+(0.10x0.5)+(0.10x0.7)+(0.05x1)+ (0.10x0.5) = 0,59

Table 13. Ranking Results

Data Alternative	SAW Results	Ranking
Learner 1	1,76	1
Learner 2	0,78	2
Learner 3	0,77	3
Learner 4	0,72	4
Learner 5	0,59	5

3.3. Evaluation Model

At the evaluation stage, researchers analyze the model and performance of the method by looking at the accuracy value and the results of the accuracy test conducted. Checking training data performance on the Naïve Bayes Algorithm in Weka gets an accuracy result of 95.172% in Table 14.

Table 14. Training Data Accuracy

```
Correctly Classified Instances         217               95.1754 %
Incorrectly Classified Instances        11                4.8246 %
Kappa statistic                          0.9027
Mean absolute error                      0.1323
Root mean squared error                  0.2197
Relative absolute error                 26.7514 %
Root relative squared error             44.1769 %
Total Number of Instances              228

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.944    0.039    0.967      0.944    0.956      0.903    0.985     0.990     Ya
                 0.961    0.056    0.933      0.961    0.947      0.903    0.985     0.980     Tidak
Weighted Avg.    0.952    0.047    0.952      0.952    0.952      0.903    0.985     0.985
```

Table 15 Although the results of testing the accuracy of testing data on Rapid Miners create precisely one hundred percent accuracy.

Table 15. Testing Data Result

accuracy: 100.00%

	true true	true false	class precision
pred. true	2	0	100.00%
pred. false	0	3	100.00%
class recall	100.00%	100.00%	

The test results of testing data in Rapid Miner follow manual calculations. Where five testing data, two classes are categorized as 'TRUE = Achievement' and three classes are categorized as 'FALSE = Not Achievement'. The final results of SAW method testing with the test data value

https://doi.org/10.31849/digitalzone.v15i1.19746

of *MA Tanwirul Qulub Tanggungan* students, from the testing data, the highest score is in Table 16.

Table 16. SAW Method Performance Results

EXPERT		SAW	
Alternative	**Rank**	**Alternative**	**Rank**
A1	1	A1	1
A2	2	A2	2
A3	3	A3	3
A4	4	A4	4
A5	5	A5	5

Accuracy = $\frac{number\ of\ similarities\ in\ student\ ranking\ data}{number\ of\ data}\ x\ 100$

Naïve Bayes Accuracy = $\frac{5}{5}\ x\ 100\%$

SAW = $\frac{5}{5}\ x\ 100\%$

Based on the validation results using the naive Bayes and simple additive weighting methods, it can be seen that the accuracy test results that have been carried out using the student data set produce an accuracy value of 100%. From the test results, it can be seen that the percentage of accuracy levels tends to increase compared to previous research [23] which applies the C4.5 Algorithm in the Selection of Outstanding Students at SMPN 10 Medan with the tree method. In the Selection of Outstanding Students at SMPN 10 Medan with the decision tree method, the accuracy value is 56.17%, precision 55.28% and recall 31.25%. The results of this study also increased the accuracy value when compared to other studies [24] which used the Weighted Product (WP) method to determine student achievement students at SMK Al-Qodiri Jember by determining the weight of each criterion as a consideration resulting in an accuracy value of 80%. Each criterion as a consideration produces an accuracy value of 80%.

4. Conclusion

Based on the research conducted, the decision support system by applying a combination of the Naive Bayes Method and the Simple Additive Weighting Method can assist schools in providing recommendations for decision-making to determine outstanding students and be able to increase the effectiveness of learning and student development programs at schools. Compared to previous research on determining student achievement, the combination of Naive Bayes and SAW methods offers several advantages. The Naive Bayes method allows initial classification based on the probability of various criteria. This is particularly suitable for data that has a non-linear relationship between variables, providing accurate initial predictions. Furthermore, the SAW method is used to assign weights to each criterion, allowing for a more structured and comprehensive assessment. SAW is effective in handling criteria that are many and have varying importance. From the accuracy test conducted, the accuracy value is 100%. The implementation of this system can help schools in performing computational calculations with high flexibility from the amount of data, data changes, the number of criteria, and the level of importance quickly and easily.

References

[1] M. T. del Val Núñez, A. de Lucas Ancillo, S. Gavrila Gavrila, and J. A. Gómez Gandía, "Technological transformation in HRM through knowledge and training: Innovative business decision making," Technol. Forecast. Soc. Change, vol. 200, p. 123168, 2024, https://doi.org/10.1016/j.techfore.2023.123168

[2] M. Núñez-Canal, M. de las M. de Obesso, and C. A. Pérez-Rivero, "New challenges in higher education: A study of the digital competence of educators in Covid times," Technol. Forecast. Soc. Change, vol. 174, p. 121270, 2022, https://doi.org/10.1016/j.techfore.2021.121270
[3] U. Azmiyah and A. P. Astutik, "The Role of The Movement Teacher in Preparing Indonesia's Excellent Generation," Nazhruna J. Pendidik. Islam, vol. 4, no. 2, pp. 396–408, 2021, doi: 10.31538/nzh.v4i2.1582.
[4] A. Nurdin, S. A. A. Samad, M. Samad, and F. Fakrurrazi, "Government Policy Regarding Education in Indonesia: Analysis of Competence-Based Curriculum, Educational Unit Level Curriculum, and Curriculum 2013," J. Gov. Soc. Policy, vol. 4, no. 1, pp. 139–155, 2023, doi: 10.24815/gaspol.v4i1.31812.
[5] A. U. Kurnia, A. S. Budi, and P. H. Susilo, "Sistem Pendukung Keputusan Penerimaan Beasiswa Menggunakan Metode Naive Bayes," Joutica, vol. 5, no. 2, p. 397, 2020, doi: 10.30736/jti.v5i2.484.
[6] A. Y. Lesmana, "Penggunaan Metode Topsis Untuk Sistem Pendukung Keputusan Pemilihan Siswa Berprestasi Di Man 1 Metro," J. Teknol. Terkini, vol. 1, no. 2, pp. 1–16, 2021, [Online]. Available: http://teknologiterkini.org/index.php/terkini/article/view/31
[7] A. L. Rahman, M. Hasbi, and S. Setiyowati, "Sistem Pendukung Keputusan Untuk Pemilihan Siswa Berprestasi Dengan Metode Analytical Hierarchy Process (AHP) Dan Technique For Order Of Preference By Similarity To Ideal Solution (TOPSIS)," J. Ilm. SINUS, vol. 18, no. 1, p. 49, 2020, doi: 10.30646/sinus.v18i1.439.
[8] A. Ardiansyah, M. Hasbi, and T. Susyanto, "Sistem Penunjang Keputusan Penerimaan Siswa Baru Berprestasi Di SMP IT Surakarta Menggunakan Metode Nearest Neighbor Dan Simple Additive Weighting," J. Teknol. Inf. dan Komun., vol. 10, no. 2, p. 55, 2022, doi: 10.30646/tikomsin.v10i2.658.
[9] F. P. Dewi, P. S. Aryni, and Y. Umaidah, "Implementasi Algoritma K-Means Clustering Seleksi Siswa Berprestasi Berdasarkan Keaktifan dalam Proses Pembelajaran," JISKA (Jurnal Inform. Sunan Kalijaga), vol. 7, no. 2, pp. 111–121, 2022, doi: 10.14421/jiska.2022.7.2.111-121.
[10] K. Anin, Y. P. K. Kelen, and D. Nababan, "Sistem Pendukung Keputusan Pemilihan Siswa Berprestasi Menggunakan Metode Profile Matching Berbasis Web (Studi Kasus : SMK Negeri 1 Kefamenanu)," J. Krisnadana, vol. 2, no. 3, pp. 388–402, 2023, doi: 10.58982/krisnadana.v2i3.315.
[11] T. Widyanti, S. S. Hilabi, A. Hananto, Tukino, and E. Novalia, "Implementasi K-Means dan K-Nearest Neighborspada Kategori Siswa Berprestasi," J. Inf. dan Teknol., vol. 5, no. 1, pp. 75–82, 2023, doi: 10.37034/jidt.v5i1.255.
[12] R. Blanquero, E. Carrizosa, P. Ramírez-Cobo, and M. R. Sillero-Denamiel, "Variable selection for Naïve Bayes classification," Comput. Oper. Res., vol. 135, p. 105456, 2021, https://doi.org/10.1016/j.cor.2021.105456
[13] S. Ghosh, C. Bhowmik, S. Sinha, R. D. Raut, M. C. Mandal, and A. Ray, "An integrated multi-criteria decision-making and multivariate analysis towards sustainable procurement with application in automotive industry," Supply Chain Anal., vol. 3, p. 100033, 2023, https://doi.org/10.1016/j.sca.2023.100033
[14] G. Singh and A. K. Chaturvedi, "Hybrid modified particle swarm optimization with genetic algorithm (GA) based workflow scheduling in cloud-fog environment for multi-objective optimization," Cluster Comput., vol. 27, no. 2, pp. 1947–1964, 2024, doi: 10.1007/s10586-023-04071-1.
[15] P. Subarkah, W. R. Damayanti, and R. A. Permana, "Comparison of Correlated Algorithm Accuracy Naive Bayes Classifier and Naive Bayes Classifier for Classification of heart failure," Ilk. J. Ilm., vol. 14, no. 2, pp. 120–125, 2022, doi: 10.33096/ilkom.v14i2.1148.120-125.

https://doi.org/10.31849/digitalzone.v15i1.19746

[16] F. Itoo, Meenakshi, and S. Singh, “Comparison and analysis of logistic regression, Naïve Bayes and KNN machine learning algorithms for credit card fraud detection,” Int. J. Inf. Technol., vol. 13, no. 4, pp. 1503–1511, 2021, doi: 10.1007/s41870-020-00430-y.
[17] N. A. Mansour, A. I. Saleh, M. Badawy, and H. A. Ali, “Accurate detection of Covid-19 patients based on Feature Correlated Naïve Bayes (FCNB) classification strategy,” J. Ambient Intell. Humaniz. Comput., vol. 13, no. 1, pp. 41–73, 2022, doi: 10.1007/s12652-020-02883-2.
[18] N. Rahmadani, R. Risnawati, and M. D. Sena, “Penerapan Algoritma Naïve Bayes Dalam Penentuan Kelayakan Penerima Bantuan Program Keluarga Harapan,” J. Tek., vol. 3, no. 2, p. 40, 2023, doi: 10.54314/teknisi.v3i2.1391.
[19] R. T. Aldisa, F. Nugroho, M. Mesran, S. A. Sinaga, and K. Sussolaikah, “Sistem Pendukung Keputusan Menentukan Sales Terbaik Menerapkan Metode Simple Additive Weighting (SAW),” J. Inf. Syst. Res., vol. 3, no. 4, pp. 548–556, 2022, doi: 10.47065/josh.v3i4.1955.
[20] S. K. Effatpanah et al., “Comparative Analysis of Five Widely-Used Multi-Criteria Decision-Making Methods to Evaluate Clean Energy Technologies: A Case Study,” Sustainability, vol. 14, no. 3. 2022. doi: 10.3390/su14031403.
[21] S. Nematzadeh, F. Kiani, M. Torkamanian-Afshar, and N. Aydin, “Tuning hyperparameters of machine learning algorithms and deep neural networks using metaheuristics: A bioinformatics study on biomedical and biological cases,” Comput. Biol. Chem., vol. 97, p. 107619, 2022, https://doi.org/10.1016/j.compbiolchem.2021.107619
[22] A. Rahman, M. S. Hossain, N. A. Alrajeh, and F. Alsolami, “Adversarial Examples—Security Threats to COVID-19 Deep Learning Systems in Medical IoT Devices,” IEEE Internet Things J., vol. 8, no. 12, pp. 9603–9610, 2021, doi: 10.1109/JIOT.2020.3013710.
[23] A. M. Husein and R. E. H. Hutauruk, “Penerapan Algoritma C4.5 Dalam Pemilihan Siswa Berprestasi di SMPN 10 Medan,” Digit. Transform. Technol., vol. 2, no. 1, pp. 8–11, 2022, doi: 10.47709/digitech.v2i1.1768.
[24] A. Dwi Ksatria, D. Arifianto, and S. Hidayatullah, “Sistem Pendukung Keputusan Siswa Berprestasi Menggunakan Metode Weighted Product (WP) (Studi Kasus SMK Al-Qodiri Jember) Decision Support System For Achieving Students Using The Weighted Product (WP) Method (Case Study Of SMK Al-Qodiri Jember),” J. Smart Teknol., vol. 4, no. 6, pp. 2774–1702, 2023.