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Improving the major recommendation systems: analysis of hybrid naïve bayes-based collaborative filtering and fuzzy logic

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Abstract

Major recommendation systems have been widely used to assist prospective students in choosing major that matches their interests and potential. In an effort to improve the performance of the recommendation system, this study proposed to use collaborative filtering techniques with naïve Bayes approach. In addition, this study improved the input parameters using fuzzy logic in determining the recommended majors. The methodology used started from collecting user data, including gender, academic history, interests, and other relevant attributes. The data were used to train the naïve Bayes technique by estimating the probability of feature conformity between users and students in the recommended majors. However, there were problems such as uncertainty and ambiguity in user preferences for input data. The fuzzy logic method aimed to improve the input parameters to more accurately reflect the user preferences. The results of improving the input parameters by using fuzzy logic were then used in the naïve Bayes technique to obtain recommendations for the direction that best suits the user's preferences. The final stage of this study used evaluation metrics such as precision, recall, and f1-score to measure the performance of the recommendation system in providing accurate recommendations. The use of a hybrid of naïve Bayes and fuzzy logic algorithms obtains an accuracy value of 87.27%, a precision value of 87.33%, a recall value of 87.24%, and an f1-score value of 87.26%. These results are higher than the usual naïve Bayes model applied in major recommendation systems.

1. Introduction

In the current era of information technology, many recommendation systems have been developed to facilitate decision-making, such as course recommendation systems and others. In a university context, recommender systems can be useful for introducing students to courses they may not have taken but are still relevant to them [1]. Another system that can be implemented is a major recommendation system that can be used at universities that offer a variety of study programs to prospective students. This needs to be pursued because not a few prospective students feel confused about choosing a major that suits their interests and goals. Apart from that, the case of students dropping out at the beginning of the semester is also quite significant. One of the causes of the failure was the wrong choice of major when applying to university [2]. The recommendation system for majors can support prospective student's decision-making and reduce dropout rates caused by selecting wrong major [3]. Previous research analyzed a system for determining courses in a department using association rule technique, and the results show that the model built can be adapted to academic information systems to minimize failure in selecting student majors [2].

In the recommendation system for determining majors, there are several problems that need to be considered. First, limited, inaccurate and incomplete data can result in inappropriate recommendations [4]. Additionally, overfitting, where the system only takes historical data into account without considering recent developments, can also be a problem. Biases in data or algorithms can also result in unfair recommendations. Moreover, a limited understanding of user preferences, confirmation cycles, and a lack of in-depth knowledge of majors and careers can also influence the recommendations. Rapid developments in the world of education and work, as well as privacy issues and the use of non-transparent algorithms, must also be taken into account. To overcome this problem, recommendation system developers must try to improve the data, minimize bias, and continuously update the algorithms used. Support for students to make more informed decisions that suit their desires and talents is also important [5]. To overcome this problem, a popular approach used in recommendation systems is collaborative filtering. This approach focuses on gathering preferences and information from previous users who have similar interests or preferences and providing personalized and relevant recommendations [6].

One method that can be used in a collaborative filtering approach is naïve Bayes [7]. The naïve Bayes is a classification method that utilizes the principles of probability theory to predict the category or label of a data based on existing features [8]. Although the naïve Bayes algorithm is generally used in data classification, it can be adapted and applied in recommendation systems [9][10]. A collaborative filtering approach using naïve Bayes has the potential to provide accurate and personalized key recommendations [11]. In this approach, the preferences and information collected from previous users who share the same interests or profile will be used to train the naïve Bayes model. Then, the model can predict opportunities or probabilities for prospective students to choose a major based on existing features.

In the collaborative filtering approach using naïve Bayes method, there are several things that can affect the quality of the recommendations provided. One important factor is the selection of input parameters [12]. These input parameters include features that are used to classify and predict user preferences or interests in certain majors. In the field of recommendation systems, data processing techniques, selection of appropriate data features, and classification techniques have always been a challenge to obtain the most accurate performance [13]. In addition, there are several other steps that can be taken to improve the performance of the recommendation system. Because of the limitations of the method applied, it is necessary to process the addition of other methods. The fuzzy-naïve Bayes method consists of two combined methods, namely fuzzy logic and naïve Bayes, to generate new concepts in the recommendation systems and is expected to have better performance in these systems [14]. Both of these techniques can basically be used in prediction or classification cases [15]. The use of these two methods will be used to determine the best recommendation results and is a contribution to this research.

In some cases, the input parameters supplied do not always have a definite or unequivocal value. In major recommendations, some features, such as ratings from users or compatibility with certain study programs, can have a degree of membership or degree of uncertainty that cannot be expressed in binary or discrete terms. In this case, the approach with fuzzy logic can be used to improve the input parameters in the naïve Bayes algorithm. Fuzzy logic is a paradigm that allows the use of membership values or degrees of uncertainty in information processing [16]. By using fuzzy logic, each feature in the input parameter can be represented by a membership function that maps the membership level or degree of uncertainty of the given value [17][18]. In this study, the value features of users towards majors can be represented by membership functions that describe low, medium, or high score levels.

Through the integration of fuzzy logic and naïve Bayes algorithms, we can incorporate fuzzy or uncertain information into classification and prediction processes. This allows the naïve Bayes algorithm to make decisions that are more adaptive and flexible, given the membership level or degree of uncertainty of each feature in the input parameters. By improving the input parameters for modeling the naïve Bayes algorithm using fuzzy logic, a collaborative filtering approach can provide users with more accurate and relevant recommendations. The ability of these algorithms to handle the level of uncertainty and ambiguity in the input parameters can help produce recommendations that are more personalized and according to individual preferences. In this study, experiments and tests were carried out to compare the performance of recommendation systems based on fuzzy-naïve Bayes with traditional naïve Bayes approaches. It is hoped that a recommendation system that uses fuzzy logic will provide better performance and improve the user experience of receiving relevant and personalized recommendations.

The first step in this research was to collect all data related to students, including gender, grades at school, interests, talents, and other relevant variables. The collected data formed the basis of subsequent analysis, and the proposed method were used to analyze this data. The analysis results were saved as training data for use in the next phase. Therefore, when there is testing data from new students with the same parameters, this data will be entered into the system, and the closeness between this data and previously stored training data will be calculated. The result will be a probabilistic value indicating the extent to which the test data matches the training data. This highest probabilistic value will be the decision result of the proposed system, which will provide major recommendations in accordance with the entered data, helping students make more informed decisions in selecting a major.

2. Research Method

The methodology used for the recommendation system used a combination of naïve Bayes algorithms and improved input parameters with fuzzy logic. The flowchart of the research conducted can be seen in Figure 1 below.

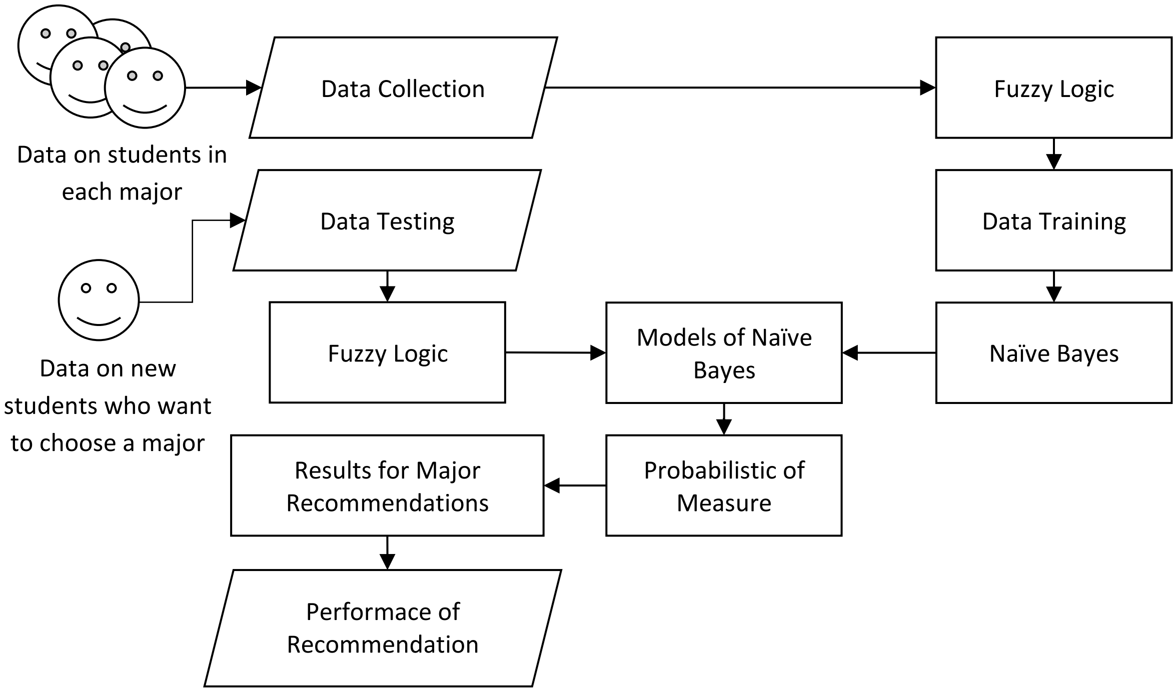

Figure 1. The Proposed Method in Major Recommendation Systems using Collaborative Filltering

2.1 Data Collection

This study used data taken directly from students at Prima Indonesia University in the informatics engineering and information systems study program. The amount of data used was 182 students, which were divided into 2 groups, namely training data and testing data, with a data distribution of 70:30. The training data was used to build a model of the proposed recommendation system, and the test data was used to determine the performance of the proposed method. The dataset information used in this study can be found in Table 1 below.

Table 1. Information of Dataset

Variable	Value
Gender (X_1)	• Male (M) • Female (F)
Math value (X_2)	65 – 100
Indonesian value (X_3)	65 – 100
English value (X_4)	65 – 100
Majors in SMA/SMK (X_5)	• Natural science (NS) • Social science (SS) • Computer network engineering (CNEn) • Software engineering (SoEn) • Multimedia (MM) • Electrical science (ES) • Others (O)
Capabilities (X_6)	• Game & mobile apps (GMA) • Web & multimedia (WM) • Intelligent computing (IC) • Network security (NS) • Business intelligence (BI) • Online marketing (OM) • Information system security (ISS) • Enterprise resource planning (ERP)
Job interest (X_7)	• IT solutions (ITS)

Majors (Y)	• IT architect (ITA) • Software engineer (SEn) • Database engineer (DBEn) • System engineer (SyEn) • E-business specialist (EBS) • Informatics engineering (IE) • Information systems (IS)

The data collection process was carried out using a Google form that contained questions regarding information about students studying at Prima Indonesia University in the informatics engineering and information systems study program.

2.2 Collaborative Filtering

Collaborative filtering (CF) is a fairly popular approach in recommendation systems to produce a decision for users by looking at similar interests or preferences of previous users. This approach illustrates that users who had similar interests and preferences in the past are likely to have similar preferences in the future [4][19]. There are several advantages from using collaborative filtering techniques, such as the ability to provide personalized and adaptive recommendations, even for users who have unique preferences. In addition, this technique can work well in dealing with data void issues, where user preferences are only available for a small subset of items [20]. Recommendation systems based on collaborative filtering have two forms: user-based and item-based. User-based considers that a good way to find items that users are interested in is to find other users who have the same interests based on user similarities, and then each rating value from the closest user will be used as a recommendation for other users [21].

The use of a recommendation system using the CF method has been widely applied in the business environment as well as in the academic world [22]. In this study, the application of user-based collaborative filtering techniques in the recommendation system of majors was carried out by utilizing preferences and similarities in values, talents, and work interests to produce appropriate recommendations between prospective students who were confused about choosing majors and students who were currently studying in the same major. Through broader user data and identifying similar users, the system can provide more personal and accurate recommendations for prospective students on majors that match their interests and potential. This can have an impact on student achievement and help students avoid dropping out due to the selection of wrong major. An overview of the use of the CF technique in this study can be seen in Figure 2 below.

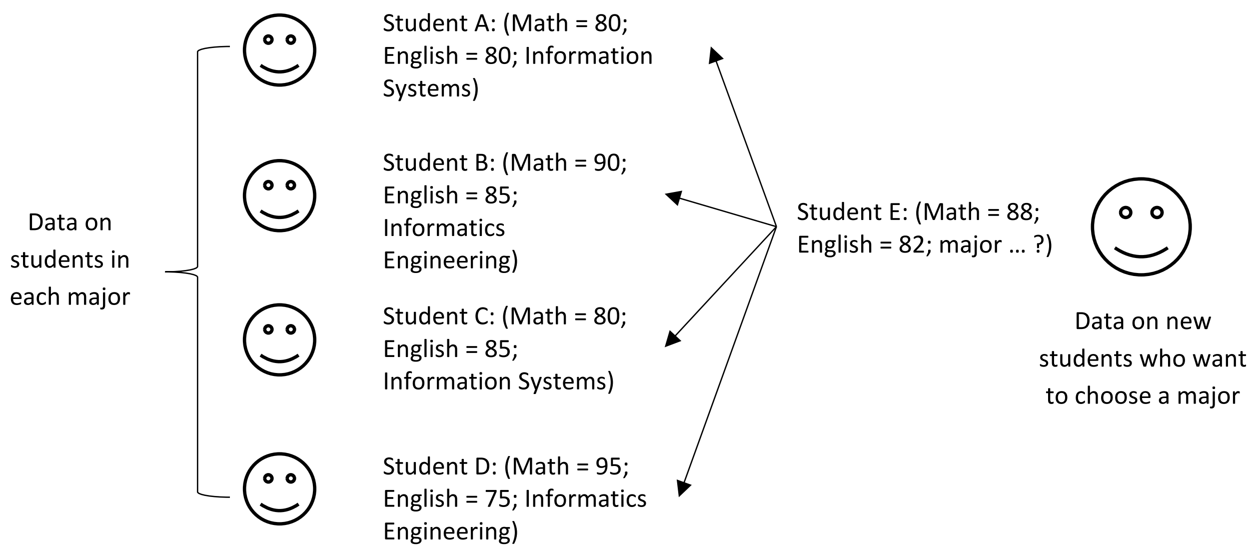

Figure 2. The Collaborative Filtering Method Illustration

2.3 Fuzzy Logic

Fuzzy logic can be used to improve the input parameters of the naïve Bayes algorithm in the recommendation system. Fuzzy logic enables the representation and handling of uncertainty or ambiguity in data [23]. In the context of a major recommendation system, fuzzy logic can assist in modelling the preferences of prospective students, who are not binary in nature but tend to have varying degrees of inclination or membership in various features or attributes. By using fuzzy logic, the input parameters in the naïve Bayes algorithm can be improved by expanding the data representation into fuzzy values. Relevant features can be given a membership weight (membership function value) or a trend level that reflects the extent to which prospective students are interested in these attributes. In addition, fuzzy logic can also assist in modelling complex relationships between features. There are several features that are interrelated or have a reciprocal influence on the preferences of prospective students towards majors. By using fuzzy logic rules, the relationship between features can be expressed in the form of linguistic rules that describe the relationship [24]. To find the value of the membership function with fuzzy rules, see Equation 1 below [25][26].

$$\mu_{1,2,3}(x,a,m,b) = \begin{cases} 0, & x \le a \\ \frac{x-a}{m-a}, & a \le x \le m \\ 1, & x = m \\ \frac{b-x}{b-m}, & m \le x \le b \\ 0, & x \ge b \end{cases} \quad (1)$$

Where: $\mu_{1,2,3}$ = Membership function value, x = Data value, a = Lowest range value, m = Middle value, and b = Highest range value.

After obtaining the value of the membership function, the next step is to find the maximum value obtained to make the decision that the data is included in the specified category. The equation used can be seen in Equation 2 below [25].

$$y = max[\mu_1, \mu_2, \mu_3] \quad (2)$$

2.4 Initialize Input with Fuzzy Logic

The use of fuzzy logic in this study aimed to improve the recommendation system input by converting numerical features into linguistic variables in the assessment of mathematics, Indonesian, and English. The results obtained show that each feature that was changed with fuzzy produced three assessment categories, namely: low, medium, and high. The conversion process carried out can be seen in Figure 3 below.

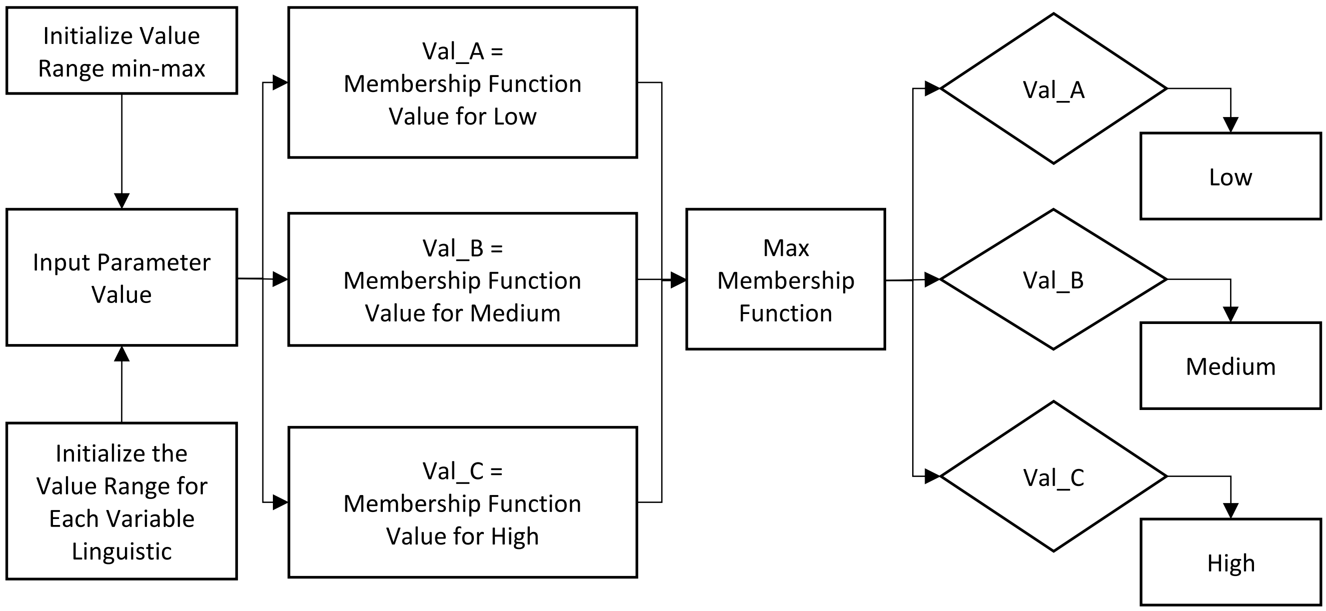

Figure 3. The Process of Initialising Input with Fuzzy Logic

By using the rules in Figure 3, converting data from numerical values to linguistic variables using fuzzy equations produces values that can be seen in Table 2 below.

Table 2. Dataset using Fuzzy Logic

No.	Name	X_1	X_2	X_3	X_4	X_5	X_6	X_7	Y
1	Student 1	F	medium	high	low	SS	BI	SEn	IE
2	Student 2	M	low	medium	medium	SS	OM	DBEn	IS
…	….	…	…	…	…	…	…	…	…
181	Student 181	M	medium	low	medium	SoEn	WM	EBS	IS
182	Student 182	M	high	high	high	O	GMA	ITA	IE

2.5 Naïve Bayes

The naïve Bayes algorithm is a machine learning technique for classifying data that can be applied to produce personalized and relevant recommendations to users in a recommendation system [7][8][9][11][27]. Although the naïve Bayes algorithm is more commonly used in data classification, it can be adapted to support recommendation problems by utilizing user preference information and other relevant features. The naïve Bayes algorithm works by assuming that each attribute used is independent from one another, although this assumption is often not true in practice. However, naïve Bayes remains effective in many cases and can provide good results in modeling user-based collaborative filtering [28].

The naïve Bayes algorithm in this study makes use of relevant features in predicting the preferences of prospective students towards students who have taken certain majors. In its use, prospective student preference data and information about students in certain majors, such as abilities, interests, and other assessments, are used as the basis for training the naïve Bayes model. The model will calculate the class probability between prospective students and existing students based on the features provided. After going through the training phase, the model can be used to make predictions on test data or prospective student data. The results of this prediction can then be used to provide major recommendations to prospective students based on their preferences and interests. Even though naïve Bayes has simple assumptions such as feature independence, this algorithm can be a useful first step in providing major recommendations to prospective students.

The use of the naive Bayes algorithm in a recommendation system may not result in optimal performance, especially if the recommendation dataset is very large, or if user preferences are very dynamic. However, with the right combination with other methods or with the use of enhancement techniques such as dimensionality reduction or changing feature weights, the naïve Bayes algorithm can make a valuable contribution to build an effective and efficient recommendation system [29]. The general equation in the naïve Bayes algorithm can be seen in Equation 3 below [30].

$$P(H|X) = \frac{P(X|H)}{P(X)} . P(H) \tag{3}$$

Where: P(H|X) = The probability of hypothesis H based on condition X, P(X|H) = The probability of X is based on the condition in the H hypothesis, P(H) = The probability of hypothesis H, and P(X) =The probability of X.

The application of the naïve Bayes algorithm in a recommendation system with collaborative filtering techniques can be seen in Figure 4 below [28].

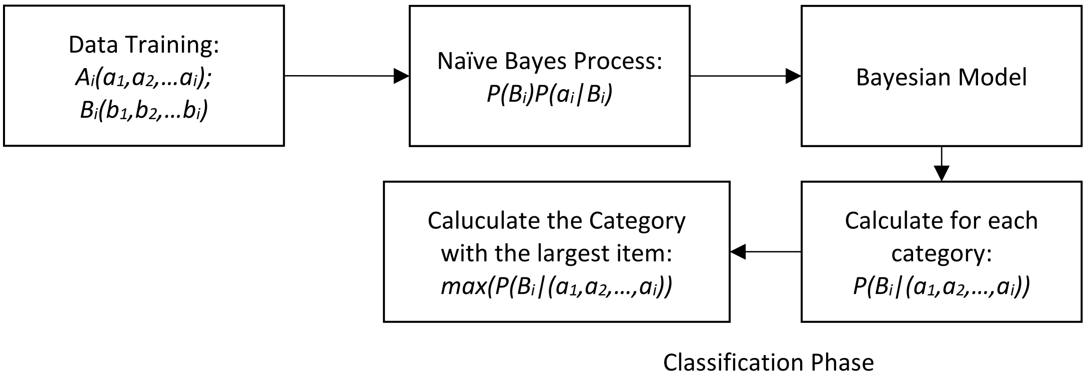

Figure 4. The Collaborative Filtering Method using Naïve Bayes

2.6 Performance Evaluation

Performance evaluation of the recommendation system in this study used relevant confusion metric techniques, such as accuracy, precision, recall, and f1-score. Accuracy is a measure of how well the model can classify data correctly. Precision is a measure of the proportion of data that is classified correctly out of all data that is classified as a certain class. Recall is a measure of the proportion of data that is correctly classified from all data that should be classified as a certain class. The f1-score is a measure of the balance between precision and recall [24]. To calculate the performance of the method used in this study, this study used the following Equation 4, Equation 5, Equation 6, and Equation 7 [31][32].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision \times Recall} \tag{7}$$

Where: TP = True Positive, TN = True Negative, FP = False Positive, and FN = False Negative.

3. Results and Discussion

This section will explain the results obtained using the method proposed in the major recommendation systems. In addition, it will also explain the results of each stage carried out and end with the achievement of increased performance from the proposed method compared to the naïve Bayes method in the recommendation systems.

3.1 Recommendation Performance Results

Improving the recommendation system's performance results is the main goal of this study. Evaluation is in the form of a confusion matrix used in the form of accuracy, precision, recall, and f1-score, which will be calculated to determine the performance of the proposed method using the usual naïve Bayes method in the recommendation system. The test was carried out with 55 student data points taken from previously collected data and the results of the recommendations provided by the system. In this study, the error value (SSE) obtained from each method used is also presented. The SSE results from the method used can be seen in Figure 5 below.

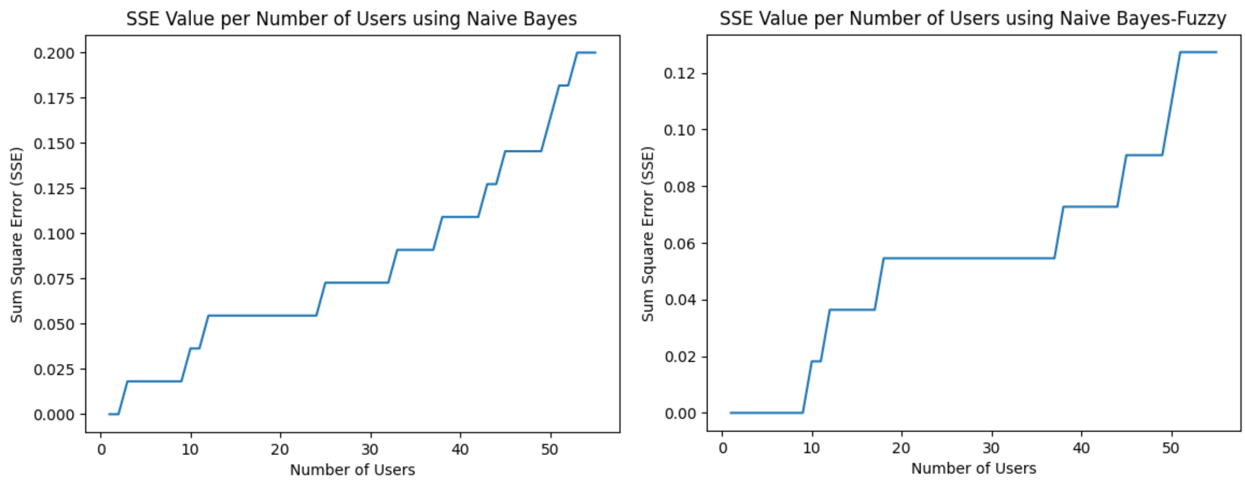

Figure 5. The Comparison of SSE Values

From Figure 5, the SSE results using the fuzzy-naïve Bayes method obtain a yield of 0.12%. Whereas using the naïve Bayes method usually obtains an SSE of 0.20%. This shows that the naïve Bayes-fuzzy method has better performance in reducing yield errors or discrepancies between the recommendations of the given majors and user preferences. With a lower SSE, the proposed method is able to provide recommendations for majors that are more in line with individual interests and needs. In addition, the lower SSE results obtained from the naïve Bayes-fuzzy method show the potential of using this method to improve the quality and accuracy of results in the major recommendation systems.

After that, the accuracy, precision, recall, and f1-score values were calculated from the data that has been tested to find out the performance of each method used in the major recommendation systems. The test results obtained can be seen in Table 3 below.

Table 3. The Comparison Recommendation Performance Results

Methods	No. of Correct	Accuracy	Precision	Recall	F1-Score
Naïve Bayes	44	80.00%	80.38%	79.89%	79.98%
Naïve Bayes + Fuzzy Logic	48	87.27%	87.33%	87.24%	87.26%

From Table 3, it is known that the proposed method provides better performance than the usual naïve Bayes method. The accuracy value of the proposed method is 87.27%, the precision value is 87.33%, the recall value is 87.24%, and the f1-score value is 87.26%. Whereas by using the usual naïve Bayes model, the accuracy obtained is 80.00%, the precision value is 80.38%, the recall value is 79.89%, and the f1-score value is 79.98%. From this comparison, it can be seen that the performance of fuzzy logic in naïve Bayes can improve the performance of the recommendation systems and give good impact. This shows that the use of the fuzzy-naïve Bayes algorithm results in a significant increase in performance compared to the usual naïve Bayes method used in the major recommendation systems. This improvement can be interpreted as an increase in the ability of the proposed method to obtain more accurate recommendation system performance and minimize errors in the major recommendation systems. With a significant increase in all evaluation metrics, it can be concluded that the fuzzy-naïve Bayes algorithm has a better ability to classify data compared to ordinary naïve Bayes. This shows the potential of the proposed algorithm to be used in various applications that require data analysis and classification with a naïve Bayes approach and fuzzy logic.

3.2 Discussion

Collaborative filtering is a popular method in recommendation systems that uses information from users who have similar preferences to generate suitable recommendations. Through this approach, similar user behaviors will be used to identify patterns and similarities between them. In this case, naïve Bayes can be used as a classification algorithm to find the relationship between prospective students and student preferences in the recommended majors. Naïve Bayes is a classification algorithm based on Bayes' Theorem with the assumption that the observed features are mutually independent. In the context of the recommendation of majors, naïve Bayes can be used to classify students' behavior based on their historical data, such as the majors they have attended before and their preferred interests and jobs. Naïve Bayes can help identify student behavior patterns and can be used by prospective students in choosing the appropriate major.

In addition, improving the performance of the recommendation system is very important to create an optimal system for providing recommendations. This study uses additional fuzzy logic methods to accommodate elements of uncertainty or ambiguity in the input parameters in the recommendation process for major. In this context, fuzzy logic is an effective solution to overcome situations where student assessments cannot be explained explicitly or fall into clearly defined categories. By applying fuzzy logic, the recommendation system can provide recommendations that are more adaptive and flexible, according to the unique characteristics of each student.

Data on previous student assessments in mathematics, Indonesian, and English will be changed using fuzzy rules so that they can be used in training the naïve Bayes model. By using fuzzy rules, the assessment data will be converted into linguistic values that reflect the level of success in each lesson. In addition, the use of this method has the function of minimizing the input value in the proposed recommendation system. This allows the naïve Bayes model to take uncertainty into account in judgments and achieve more accurate predictions.

By integrating fuzzy logic and naïve Bayes, the recommendation system can produce recommendations that are more personal and relevant based on the preferences and abilities of each student. This approach strengthens the recommendation system's ability to understand and adapt to individual needs, thereby enhancing the user experience and helping students make informed decisions about the major they wish to choose. A combined approach between collaborative filtering based on naïve Bayes and fuzzy logic can help improve the quality of major recommendations by utilizing previous student behavior information and incorporating an element of uncertainty.

By using this approach, students are expected to be able to find majors that are more relevant to their needs and preferences, thus increasing the effectiveness of their learning based on the majors they have chosen. While this hybrid approach shows good potential, there are challenges that need to be overcome. One of them is the processing of large and complex data, especially when large user data is involved. In addition, problems such as the cold-start problem (when there is not enough user data available) and the sparsity problem (when the user preference data is very sparse) also need attention. Opportunities for further development include the use of other techniques and algorithms, such as deep learning, to improve the quality of recommendations.

4. Conclusion

Based on the results obtained, the hybrid approach that combines naïve Bayes with fuzzy logic in the major recommendation system obtains good performance. This approach offers advantages for improving the quality of major recommendations by taking user preferences and collaborative information into account. The proposed method gives better performance than the usual naïve Bayes method. The accuracy value of the proposed method is 87.27%, the precision value is 87.33%, the recall value is 87.24%, and the f1-score value is 87.26%. Whereas by using the usual naïve Bayes, the accuracy obtained is 80.00%, the precision value is 80.38%, the recall value is 79.89%, and the f1-score value is 79.98%. From this comparison, it can be seen that the performance of fuzzy logic in naïve Bayes for the recommendation system has a good impact on the performance of the proposed system. Further research could focus on exploring the use of this hybrid approach on a broader scale with larger and more diverse data sets. In addition, the research can be focused on developing more sophisticated and adaptive fuzzy logic algorithms to increase the precision of recommendations, as well as on integrating more complex artificial intelligence elements to increase the personalization of recommendations based on recent developments in the field of artificial intelligence.

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