Decision Support System to Determine *Uang Kuliah Tunggal* (UKT) by Combining Naïve Bayes Classifier and Fuzzy-TOPSIS

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Abstract. *Uang Kuliah Tunggal* (UKT) is a portion of the single tuition fee that is borne by each undergraduate student at a state university in Indonesia. UKT is the number of fees that have to be paid by students in each semester. Basically, UKT is implemented to impose tuition fees according to the income and the condition of students’ families. However, there is an issue in regard to the inappropriate classification of UKT. This issue is caused by several factors such as manual method is still used in determining UKT Classes and there is likely an element of subjectivity in determining UKT Classes of new students. Based on these issues, a decision support system that can determine UKT Class of new students is needed. The Naïve Bayes Classifier (NBC) method is used to classify data into eight UKT Classes. Whereas Fuzzy-TOPSIS is used in the optimization selection process of UKT Class 1 to 8. This method was chosen for its capability in choosing the best alternative out of several possibilities, in this case, the intended alternative is the most suitable new student to be selected in UKT Class based on six predetermined criteria. Research results show that the NBC Model can identify UKT groups of students with mean values of precision and recall testing are 77.8% and 77.8% and the model accuracy is 77.8% as well. In optimization selection process of UKT using Fuzzy-TOPSIS results obtained the percentage of UKT 1 group recommendations was 5.33%, UKT 2 was 5.33%, UKT 3 was 10.22%, UKT 4 was 24.89%, UKT 5 was 24.89%, UKT 6 was 10.22%, UKT 7 was 10.22% and UKT 8 was 8.00%. Based on the results above, it can be concluded that the combination of Naïve Bayes Classifier and Fuzzy-TOPSIS can be implemented for determining the UKT Classes. Then the recommendations of the UKT Classes can be considered in determining the UKT Classes of students for the Decision-maker.

1. Introduction

In the Regulation of the Minister of Research, Technology and Higher Education of the Republic of Indonesia Number 39 of 2017 regarding the Single Tuition Fees and *Uang Kuliah Tunggal* (UKT) within the Ministry of Research, Technology, and Higher Education domain, it is explained that *Uang Kuliah Tunggal* (UKT) is a fee borne by each student based on their financial ability at a state university (Permenristekdikti No. 39 of 2017). The aims of the UKT implementation are to ease the payment process of tuition fees and to eliminate additional costs that are difficult for the State to monitor [1].

UKT is carried out by classifying new students according to their financial condition [1][2]. UKT is divided into eight classes, from UKT 1, which is the lowest UKT, to UKT 8, which is the highest UKT.
(Permenristekdikti No. 39 of 2017). Students who are less fortunate get the lower category than the fortunate ones. However, ever since the UKT was implemented, state universities have faced a serious issue regarding inappropriate classifications. The causes of this problem include the computer system built to determine UKT Classes was not tested or even still using manual methods and also there is an element of subjectivity in determining UKT Classes of new students. In determining UKT Classes of new students, state universities conduct interviews with each new student by looking at several criteria that represent the financial ability of their parents [1][2][3]. In practice, determining UKT Classes of new students in a state university is very dependent on the evaluation of each interviewer. Coupled a quite large amount of data, state universities will have difficulties when using interviews in identifying UKT Classes for each student. Therefore, state universities need an effective way of determining UKT Classes of new students as a recommendation to help them analyze data obtained from the socio-economic conditions of each student's parents. In categorizing students into existing UKT Classes that are in accordance to their financial ability, there are some things need to be carried out such as developing the detail of the criteria which support filtering and classifying a student into UKT categories according to their financial abilities and most importantly is to involve the advance of information technology in developing a decision support system to determine students’ UKT.

The Naïve Bayes Classifier method is used to determine the categorization of teacher performance feasibility [4][5][6][7]. The data input came from teachers’ data of SMPN 1 Jabon Sidoarjo. As much as 46 data are used which are divided into two datasets, namely 36 training data and 10 testing data. A study using the Naïve Bayes Classifier (NBC) method also helped credit analysts to select customers who truly meet the requirements for credit release in order to avoid bad credit problems. NBC calculates the probabilities of one class from each attribute class and determines the most optimal class [5].

In the process of ranking alternatives to be chosen, the Fuzzy-TOPSIS method is used to solve a mining-truck selection issue. The method is transparent and easily comprehended and applied by decision-makers [8]. Research conducted by Nursikuwagus [9], Fuzzy-TOPSIS implementation in measuring student competence is an effective process as well. Its performance simplicity has made Fuzzy-TOPSIS suitable for numerical datasets [9][10]. In a study on head of village election, it is concluded that determining the head of the village performance index can be done using the Fuzzy-TOPSIS method as the decision support system [11].

Based on this background, the case in this research is to design and implement the Decision Support Systems (Decision Support Systems) for UKT classes selection in a University. The objective of this research is to create a Decision Support System to determine UKT Classes by combining the Naïve Bayes Classifier and Fuzzy-TOPSIS method. These two methods are used because they have been widely applied to support grouping and ranking on Decision-making issues.

2. Previous Research
The previous study on UKT has also been conducted at the University of Sembilan Belas November Kolaka. UKT Classes are divided into five classes with the number of Class 1 and Class 2 are as much as 5% of the number of new students. Therefore, methods that can help to determine the UKT Classes are needed. The said methods are Fuzzy C-Means and MADM Yager Model. Based on a study result, the system for determining UKT Classes with a combination of Fuzzy C-Means and MADM Yager Model can display the status of each class or as a whole [12]. In addition, a study related to determining UKT at IAIN Zawiyah Cot Kala Langsa, divided UKT Classes into 3 (three) categories, where the quota of students who can enter Class 1 is limited to 10% of the number of new students [13]. Based on the case, the Naïve Bayes Classifier method is used to classify data into three UKT Classes. Whereas AHP TOPSIS is used for the UKT Class 1 selection process, so that there is only 10% of the total new students remaining. This method is chosen for its ability to choose the best alternatives out of several possibilities, in this case, the most feasible new students in UKT Class 1 based on specified criteria [13].
3. Research Method
In general, the Naïve Bayes Classifier (NBC)-Fuzzy TOPSIS method flowchart is shown in Figure 1.

![Flowchart of NBC-Fuzzy TOPSIS](image)

Figure 1. Flowchart of NBC-Fuzzy TOPSIS.

4. Results and Discussion
4.1. System Design
The system designed in this research is a system that can classify a single tuition fee called “UKT” for new students at University of Jambi. The methods used are Naïve Bayes Classifier (NBC) and Fuzzy-TOPSIS. These three methods are combined in solving the problem of determining the UKT Classes. NBC method is used for UKT classification process. The Fuzzy-TOPSIS is used to optimize the NBC classification results based on applicable regulations and the results are used for recommendations in determining UKT classes for new students. The first step is criteria input or attributes classification using parameters such as parents’ income, the number of parents’ dependents, and electricity bills. The output of NBC calculation results is the probability value of each class and the results of the UKT classification of new students based on the highest grade of probability values [13].

After the data is inputted, results of determining UKT Classes are directly counted and the results of this process will classify students into 8 classes of UKT. If the results of UKT 1 have exceeded 5% of the total new students, then UKT optimization is needed using the Fuzzy-TOPSIS method so that only 5% of the new students remain in UKT 1, whereas the remaining number goes to UKT 2. If the results of UKT 2 have exceeded 5% of the total new students (without UKT 1), then UKT optimization is needed using the Fuzzy-TOPSIS method so that only 5% of the new students remain in the UKT 2, whereas the remaining number goes into UKT 3 and so on with the conditions shown in Table 1 below.

| UKT Class | Percentage | UKT Class | Percentage |
|-----------|------------|-----------|------------|
| UKT 1     | 5%         | UKT 5     | 25%        |
| UKT 2     | 5%         | UKT 6     | 10%        |
| UKT 3     | 10%        | UKT 7     | 10%        |
| UKT 4     | 25%        | UKT 8     | 10%        |
4.2. Naïve Bayes Classifier (NBC)
Shown below are the NBC steps:

4.2.1. The training data collection. In this step, training data of each UKT Classes are collected to form NBC model. The description of the training data can be seen in Table 2.

Table 2. UKT Classes Training Data.

| No | Ph    | RL    | JT | UKT Class |
|----|-------|-------|----|-----------|
| 1  | 500.000 | 103.000 | 4 | II        |
| 2  | 500.000 | 75.000  | 2 | II        |
| 3  | 500.000 | 22.000  | 3 | II        |
| ... | ...     | ...    | ... | ...       |

4.2.2. Determining mean value ($\mu$) of each attribute towards classes. Furthermore, the attribute value in Table 2 is used for the calculation of the classification model by counting the mean value ($\mu$) and standard deviation ($\sigma$) of each attribute towards classes [14]. Mean value is shown in equation $\mu = \frac{1}{n} \sum_{i=1}^{n} x_i$ and the result is shown in Table 3.

Table 3. Mean value ($\mu$).

| Class   | Mean ($\mu$) |
|---------|--------------|
| Ph      | JT           |
| UKT 1   | 450.000      | 1.5          |
| UKT 2   | 633.333.3    | 1.19         |
| UKT 3   | 1,350,983.3  | 1.1          |
| UKT 4   | 2,507,361.1  | 1.583        |
| UKT 5   | 3,291,060    | 1.4          |
| UKT 6   | 4,500,160    | 1.3          |
| UKT 7   | 3,791,012.5  | 1.5          |
| UKT 8   | 7,371,718.3  | 1.321        |

4.2.3. Determining standard deviation ($\sigma$) of each attribute towards classes. The standard deviation of each attribute towards UKT classes is calculated by using equation $\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \mu)^2}$ [14]. The standard deviation of each attribute towards classes is shown in Table 4.

Table 4. Standard deviation ($\sigma$).

| Class   | Standard Deviation ($\sigma$) |
|---------|-----------------------------|
| Ph      | JT | RL |
| UKT 1   | 0  | 0.707 | 3535.534 |
| UKT 2   | 219848.433 | 0.75 | 59232.512 |
| UKT 3   | 357423.05 | 0.752 | 68623.748 |
| UKT 4   | 785580.301 | 1.156 | 61506.12 |

4.2.4. The calculating class prior value. After mean value and standard deviation are obtained, the calculation is carried out to get the prior value, which is shown in equation $P(C_i) = \frac{N_c}{N}$ [15]. Based on the number of training data on each class and the whole training data, we obtained class prior value as shown in Table 5.
Table 5. Class prior.

| Class | Class prior | Class | Class prior |
|-------|-------------|-------|-------------|
| UKT 1 | 0.0089      | UKT 5 | 0.0444      |
| UKT 2 | 0.0933      | UKT 6 | 0.0444      |
| UKT 3 | 0.2667      | UKT 7 | 0.0356      |
| UKT 4 | 0.16        | UKT 8 | 0.3467      |

From the result of students’ UKT classification using formed NBC model, the percentage of UKT Class is obtained as shown in Table 6.

Table 6. Percentage of UKT Class Using NBC.

| UKT Class | Number of students | Percentage (%) | UKT Class | Number of students | Percentage (%) |
|-----------|--------------------|----------------|-----------|--------------------|----------------|
| UKT 1     | 2                  | 0.89           | UKT 5     | 10                 | 4.44           |
| UKT 2     | 21                 | 9.33           | UKT 6     | 10                 | 4.44           |
| UKT 3     | 60                 | 26.67          | UKT 7     | 8                  | 3.56           |
| UKT 4     | 36                 | 16.00          | UKT 8     | 78                 | 34.67          |

It is noted from Table 6 that the percentage of students’ UKT Classes is not optimal yet, therefore, an optimization process on priority selection of each UKT Class using Fuzzy-TOPSIS method is needed. Hereafter, an examination process is carried out using precision and recall. The precision number is used to show the accuracy of the classification using NBC method. The recall is a value that is used as a measure for the number of relevant items obtained by NBC methods. Data for examination are obtained by comparing real data with data obtained from the system. The mean values of precision and recall testings are 77.8% and 77.8% and the model accuracy is 77.8% as well.

4.3. **Fuzzy-TOPSIS**

In this study, we carried out optimization analysis of UKT categorization using Fuzzy-TOPSIS. The first step is determining criteria and alternatives input [16]. The next steps are described below.

4.3.1. **Alternatives that have six criteria is inserted into Table 7 to elaborate the value of each criteria before being processed using Fuzzy-TOPSIS.**

Table 7. Criteria and alternative.

| No | Alternative | Income | Electricity | Responsibilities | House ownership status | Vehicle facilities | Vehicle ownership status |
|----|-------------|--------|-------------|-------------------|------------------------|-------------------|-------------------------|
| 1  | A1          | 1.000,000 | 22,000     | 1                 | MS                     | TA                | TP                      |
| 2  | A2          | 1.500,000 | 42,500     | 2                 | MS                     | SM                | MSD                     |
| 3  | A3          | 1.500,000 | 154,000    | 1                 | MS                     | TA                | TP                      |

4.3.2. **Design the criteria rank and weight.** In this step, we determine the importance of the weighting value which functions as a variable to calculate the value of $Y_{ij}$.

Table 8. Criteria ranking.

| Code | Criteria | Fuzzy set | Score | Code | Criteria | Fuzzy set | Score |
|------|----------|-----------|-------|------|----------|-----------|-------|
| Ph   | Income   | Low       | 1     | JT   | Number of | Moderate  | 2     |
|      |          | Moderate  | 2     |      | parents’ dependant | High     | 3     |
|      |          | High      | 3     |      |            | Low       | 1     |
| RL   | Electricity bill | Moderate | 2 | FK | Vehicle facility owned | Moderate | 2 |
|      |          | High      | 3     |      |            | High      | 3     |
4.3.3. Design the coupled matrix nomination. Coupled matrix nomination is obtained from data results got from criteria of which the value is from the Fuzzy set. Coupled matrix nomination is shown in Table 10.

Table 10. Coupled matrix nominations.

| Alternative | Income | Electricity bill | Dependant | Residence ownership status | Vehicle facility owned | Vehicle ownership status |
|-------------|--------|------------------|-----------|---------------------------|-----------------------|-------------------------|
| A1          | 1      | 1                | 1         | 3                         | 1                     | 1                       |
| A2          | 1      | 1                | 2         | 3                         | 2                     | 3                       |
| A3          | 1      | 2                | 1         | 3                         | 1                     | 1                       |
| …           | …      | …                | …         | …                         | …                     | …                       |

4.3.4. Matrix Defuzzification. Matrix defuzzification is carried out by changing initial value into fuzzy numbers.

Table 11. Matrix defuzzification.

| Alternative | Income  | Electricity bill | Dependant | Residence ownership status | Vehicle facility owned | Vehicle ownership status |
|-------------|---------|------------------|-----------|---------------------------|-----------------------|-------------------------|
| A1          | 0,40    | 0,15             | 0,30      | 0,15                      | 0,05                  | 0,05                    |
| A2          | 0,40    | 0,15             | 0,60      | 0,15                      | 0,10                  | 0,15                    |
| A3          | 0,40    | 0,30             | 0,30      | 0,15                      | 0,05                  | 0,05                    |
| …           | …       | …                | …         | …                         | …                     | …                       |

4.3.5. Normalize the matrix value obtained from fuzzification. In the normalizing matrix, there are two processes. The first one is to count $X_i^2$ result obtained from squared fuzzification and adding up $A_1$ to $A_{225}$ ($\sum(X_i^2)^2$). This process is done against 6 criteria, from $X_{1n}$ to $X_{6n}$. The second step is to square-root each value ($\sum(X_i^2$). These two processes are shown in Table 12 below.

Table 12. Normalization value terms.

| $X_{ij}$ | Kriteria |
|----------|----------|
| $X_{1n}$ | $X_{2n}$ | $X_{3n}$ | $X_{4n}$ | $X_{5n}$ | $X_{6n}$ |
| $\sum(X_i^2)^2$ | 158.40 | 19.28 | 77.13 | 4.94 | 3.40 | 4.62 |
| $R_{ij}$ | 12.59 | 4.39 | 8.78 | 2.22 | 1.84 | 2.15 |
After determining the normalization value, the next step is to normalize the decision matrix. The calculation is shown in equation $r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$. The results of the matrix normalization can be seen in Table 13.

4.3.6. Carry out a multiplication task upon the normalized matrix ($r_{ij}$) with importance weighting ($w_i$). The alternative calculation is carried out with six criteria. Fuzzy-TOPSIS weighting results are shown in Table 13.

| Alternative | $X_{1n}$ | $X_{2n}$ | $X_{3n}$ | $X_{4n}$ | $X_{5n}$ | $X_{6n}$ |
|-------------|----------|----------|----------|----------|----------|----------|
| A1          | 0.0127   | 0.0051   | 0.010    | 0.0101   | 0.0014   | 0.001163 |
| A2          | 0.0127   | 0.0051   | 0.041    | 0.0101   | 0.0054   | 0.010471 |
| A3          | 0.0127   | 0.0205   | 0.010    | 0.0101   | 0.0014   | 0.001163 |
| …           | …        | …        | …        | …        | …        | …        |

4.3.7. Carry out a multiplication task upon the normalized matrix ($r_{ij}$) with importance weighting ($w_i$). The alternative calculation is carried out with 6 criteria. Fuzzy-TOPSIS weighting results are shown in Table 14.

| Alternative | $X_{1n}$ | $X_{2n}$ | $X_{3n}$ | $X_{4n}$ | $X_{5n}$ | $X_{6n}$ |
|-------------|----------|----------|----------|----------|----------|----------|
| A1          | 0.0051   | 0.0008   | 0.0031   | 0.0015   | 0.0001   | 0.000058 |
| A2          | 0.0051   | 0.0008   | 0.0246   | 0.0015   | 0.0005   | 0.001571 |
| A3          | 0.0051   | 0.0061   | 0.0031   | 0.0015   | 0.0001   | 0.000058 |
| …           | …        | …        | …        | …        | …        | …        |

4.3.8. Determine the positive ideal solution ($A^+$) and negative ideal solution ($A^-$). The calculation of positive ideal solution and negative ideal solution can be seen in Table 15.

| Alternative | $X_{1n}$ | $X_{2n}$ | $X_{3n}$ | $X_{4n}$ | $X_{5n}$ | $X_{6n}$ |
|-------------|----------|----------|----------|----------|----------|----------|
| $A^+$       | 0.137299 | 0.020752 | 0.083007 | 0.001518 | 0.001829 | 0.001571 |
| $A^-$       | 0.005085 | 0.000769 | 0.003074 | 0.000056 | 0.000068 | 0.000058 |

4.3.9. Calculate the distance of positive ideal solution ($D^+$) using equation $D_i^+ = \sqrt{\sum_{j=1}^{n}(y_j^+ - y_{ij})^2}$ and calculate the distance of negative ideal solution ($D^-$) using equation $D_i^- = \sqrt{\sum_{j=1}^{n}(y_j^- - y_{ij})^2}$. As a result, the distance of positive ideal solution and negative ideal solution can be seen in Table 16.

| $D_i^+$  | $D_i^-$  |
|----------|----------|
| D1       | 0.14926  |
| D5       | 0.07617  |
| D6       | 0.07414  |
| …        | …        |
4.3.10. Calculate preferences value \( (V_i) \) for each alternative with equation \( V_i = \frac{D_i^-}{D_i^- + D_i^+} \). Then sorted from the largest to the smallest preference value whose results are shown in Table 17.

**Table 17. The results of the optimization of the UKT Class.**

| Alternative | Nilai \( V_i \) | UKT Class |
|-------------|----------------|-----------|
| D14         | 0.893          | 1         |
| D64         | 0.507          | 1         |
| D6          | 0.509          | 1         |
| …           | …              | …         |

Based on the results of the optimization of the UKT Classes using the Fuzzy-TOPSIS method, the percentage of UKT Classes recommendations obtained is shown in Table 18.

**Table 18. Class of UKT using Fuzzy-TOPSIS.**

| UKT Class | Number of students | Percentage (%) |
|-----------|--------------------|----------------|
| UKT 1     | 12                 | 5.33           |
| UKT 2     | 12                 | 5.33           |
| UKT 3     | 23                 | 10.22          |
| UKT 4     | 56                 | 24.89          |
| UKT 5     | 56                 | 24.89          |
| UKT 6     | 23                 | 10.22          |
| UKT 7     | 23                 | 10.22          |
| UKT 8     | 18                 | 8.00           |

Based on Table 18, it can be concluded that the percentage of UKT Classes of students using Fuzzy-TOPSIS becomes more optimum.

5. Conclusion

In this research, based on the results of the UKT classification of students using the NBC model formed, the percentage of UKT 1 groups was 0.89%, UKT 2 was 9.33%, UKT 3 was 26.67%, UKT 4 was 16.00%, UKT 5 was 4.44%, UKT 6 was 4.44%, UKT 7 was 3.56% and UKT 8 was 34.67%. From these results it is known that the percentage of UKT student groups is not yet optimum, so the optimization selection process prioritization is needed in each UKT group conducted by the Fuzzy-TOPSIS method. Then the testing process is carried out using precision and recall. The average precision and recall test results were 77.8% and 77.8% and the accuracy of the model was also obtained by 77.8%.

Based on the results of optimization of the UKT group using the Fuzzy-TOPSIS method, the percentage of UKT 1 group recommendations was 5.33%, UKT 2 was 5.33%, UKT 3 was 10.22%, UKT 4 was 24.89%, UKT 5 was 24.89%, UKT 6 was 10.22%, UKT 7 was 10.22% and UKT 8 was 8.00%. From these results it is known that the percentage of UKT groups of students using Fuzzy-TOPSIS becomes more optimum, then the recommendations of UKT groups can be considered in determining the UKT groups of students.

Based on the results of the discussion above, it can be concluded that the combination of Naïve Bayes Classifier and Fuzzy-TOPSIS can be implemented for determining the UKT Classes. Then the recommendations of the UKT Classes can be considered in determining the UKT Classes of students for decision-maker.

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