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Implementation of KNN and AHP-TOPSIS as Recommendation System for Mustahik Selection

Winda Aprianti[1*], Jaka Permadi[2], Herfia Rhomadhona[2], Noor Amelia[4]
[1,2,3,4]Politeknik Negeri Tanah Laut, Indonesia
[1]winda@politala.ac.id, [2]jakapermadi.88@politala.ac.id, [3]herfia.rhomadhona@politala.ac.id, [4]noor.amelia@politala.ac.id

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***Corresponding Author**

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ABSTRACT

The National Amil Zakat Agency (BAZNAS) has the task of managing zakat on a national scale, including zakat. The number of prospective zakat recipients is greater than the availability of zakat funds distributed, which has an impact on the need for a selection process for mustahik. In this research, to assist the mustahik selection process, KNN will be used to classify mustahik candidates who meet the requirements, AHP to obtain consistent weights, and TOPSIS to provide recommendations for the order of mustahik whose zakat will be distributed. The dataset used in the research consisted of 77 data consisting of the criteria for number of dependents, husband's job, wife's job, total income, total expenses, and acceptance status of mustahik candidates. The application of KNN produced 15 data that were declared worthy of being considered mustahik. In the next stage, using AHP, the weights for each criterion were obtained at 12.66%, 9.23%, 10.10%, 45.96% and 22.04%. These weights were used in the TOPSIS decision support system and the results obtained were that the 76th mustahik candidate was the first ranked candidate to be proposed as a mustahik. In this research, a system was also built using KNN and AHP-TOPSIS using the PHP programming language as a recommendation system tool.

INTRODUCTION

The National Amil Zakat Agency (BAZNAS) based on Undang-Undang Nomor 23 Tahun 2011, is the official body responsible for collecting and distributing Zakat, Infaq, and Sadaqah (ZIS). These funds are distributed to those entitled to receive zakat, known as mustahik. Mustahik are individuals who need financial support due to economic hardships, health issues, natural disasters, or other conditions that require assistance from the community or government (Maulidhinah et al., 2023). BAZNAS operates throughout all regencies in Indonesia, including Tanah Laut Regency.

BAZNAS Tanah Laut Regency is responsible for overseeing the management of zakat according to the principles of Islamic sharia, trust, benefit, justice, legal certainty, integration, and accountability. This ensures that zakat funds are managed transparently and accurately, providing a significant impact on those in need. Therefore, it is necessary to conduct a selection process to determine the recipients of zakat (mustahik), considering the large number of applicants and the limited amount of zakat funds available.

Currently, the selection process conducted by BAZNAS Tanah Laut Regency involves collecting applications from prospective zakat recipients (mustahik) through registration forms. The required data includes personal information, address, number of dependents, occupation of the husband, occupation of the wife, total income, and household expenses. Errors in data collection and the selection process of mustahik candidates are not uncommon. Thus, an information system is needed to process mustahik data more quickly and accurately using data mining (Lestari, 2020). Data mining is the process of gathering and processing data to classify prospective zakat recipients (mustahik). One classification method is the KNN Method, which can classify mustahik candidates as eligible or ineligible to receive zakat based on the number of dependents, the husband's occupation, the wife's occupation, total income, and household expenses. Subsequently, the data of mustahik candidates deemed eligible to receive zakat will be prioritized using the AHP-TOPSIS method (Rizal M, 2022). The results from this method can provide recommendations for prospective zakat recipients (mustahik).

LITERATURE REVIEW

The integration of classifiers in DSS has been explored in several studies. Singgalen (2023) conducted his research by applying the CRISP-DM and SAW methods for sentiment analysis and DSS for hotel stays. The classification algorithm used was SVM with the SMOTE algorithm, achieving an accuracy of 99.74%. Another research by Putra et al. (2016) integrated SVM with AHP-TOPSIS for selecting and recommending scholarship recipients. AHP was used for feature selection, while SVM was used for classification from three classes to two classes, and then TOPSIS was used to rank the scholarship recipient recommendations.

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In the research conducted by authors, classification is performed before running the DSS. This approach is taken to ease the workload of the DSS since the data had already been classified. The classification algorithm used is K-Nearest Neighbor (KNN). KNN is chosen for this study because of its high classification accuracy and very fast processing time, although its accuracy is not as high as popular classifiers like SVM (Adi & Wintarti, 2022). High accuracy was also demonstrated in a study by Cahyanti et al. (2020), where KNN achieved accuracy and precision above 90% in classifying datasets of breast cancer patients. The classification capability of KNN was further proven by its higher accuracy compared to several classifiers such as Random Forest Tree, Decision Tree, and Naïve Bayes (Andrian et al., 2020; Indriani, 2020; Jabbar et al., 2022).

The AHP-TOPSIS method is often implemented in research related to DSS, especially those related to determining aid recipients. Apriliani et al. (2020) implemented AHP-TOPSIS in their study on DSS for prioritizing small and medium enterprise assistance in Tegal City. The AHP method was used for weighting the criteria, and then the TOPSIS method was used to rank each alternative. Research conducted by Maulana et al. (2018) on DSS for determining poor family aid recipients showed that AHP-TOPSIS had an accuracy of 80%. Meanwhile, research by Habibah and Rosyda (2022) on DSS for recipients of village fund BLT in Pekandangan showed an accuracy of 91%.

METHOD

The research method is illustrated in Figure 1.

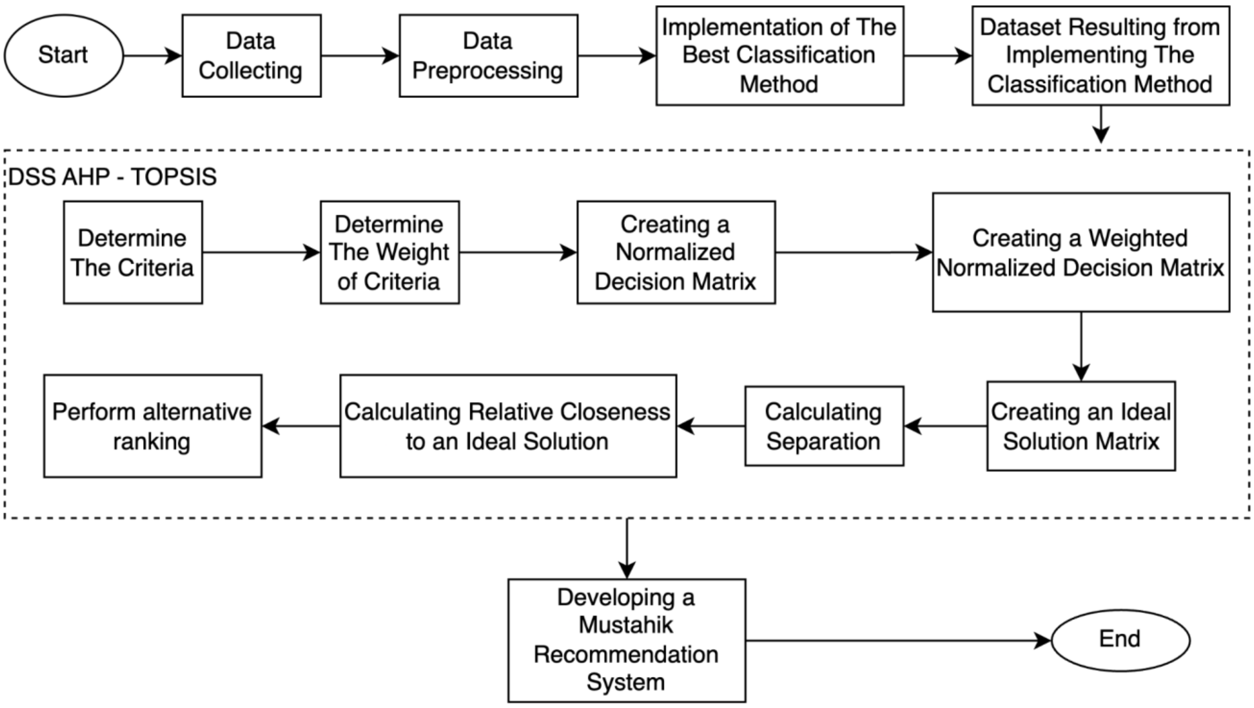

Figure 1. The Research Method

The research stages consist of data collected from BAZNAS, data preprocessing, implementation of the best classification method, implementation of decision support system, and developing system. Data preprocessing is carried out to obtain data that is free from bias, redundant data, data inconsistencies and missing value. Data preprocessing in this research, namely data transformation and normalization. Data transformation is carried out by changing categorical attributes into numerical attributes. Meanwhile, normalization is carried out by calculating each attribute using (1).

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

The third stage is implementing a classification method obtained from Amelia and Aprianti (2023), namely KNN Euclidean. The KNN method to find out which mustahik candidates are declared eligible (Amelia & Aprianti, 2023). The fourth stage is to make the dataset from the third stage as a dataset for implementing a decision support system (DSS) using AHP and TOPSIS. The steps for implementing the AHP-TOPSIS DSS are described as follows.

1. Determining criteria
2. Determine the criteria weights by applying the AHP method to ensure the determined weights meet consistency.
   a. Create a normalized comparison matrix using (2) with a_{ij} is the ith member in the jth row of the pairwise comparison matrix between criteria.

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$$r_{ij} = \frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}} \quad (2)$$

b. Calculating weight values (eigenvectors) using (3)

$$Weight_i = \frac{\sum_{j=1}^{n} a_{ij}}{n} \quad (3)$$

c. Calculate consistency using (4) to (6).

$$\lambda_{max} = \frac{\sum \frac{\sum_{j=1}^{n} a_{ij} \times Weight_i}{Weight_i}}{n} \quad (4)$$

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (5)$$

$$CR = \frac{CI}{RI} \quad (6)$$

If the CR value is less than 10%, then the comparison of criteria weights is declared consistent and can be used as a weight when applying the TOPSIS method in steps 3 to step 7.

3. Create a normalized decision matrix (R) using (7) with x_{ij} is the performance value for the ith alternative (A_i) against the jth criterion (C_j).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (7)$$

4. Create a weighted normalized decision matrix (Y) using (8) with w_j is the weight of the jth criterion.

$$y_{ij} = r_{ij} \times w_j \quad (8)$$

5. Create a positive ideal solution matrix using (9) and a negative ideal solution using (10).

$$A^+ = (y_1^+, y_2^+, \dots, y_{m-1}^+, y_m^+) \quad (9)$$

$$A^- = (y_1^-, y_2^-, \dots, y_{m-1}^-, y_m^-) \quad (10)$$

6. Calculating separation using (11) and (12).

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (y_{ij} - y_j^+)^2} \quad (11)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (y_{ij} - y_j^-)^2} \quad (12)$$

7. Calculate the relative closeness to the ideal solution (C_i^+) using (13)

$$C_i^+ = \frac{S_i^-}{S_i^+ + S_i^-} \quad (13)$$

8. Displays the alternative ranking by sorting the largest value to the smallest value.

The last stage, a system will be developed using the PHP programming language which has been implemented by KNN with AHP-TOPSIS as a recommendation system for determining mustahik.

RESULT

This classification dataset was obtained from BAZNAS, which consists of the attributes number of dependents (A), husband's job (B), wife's job (C), total income (D), total expenses (E), and the decision of the *mustahik* candidate (worthy and not feasible) as the target class. The second stage is data preprocessing. The attributes in the form of categorical data are attributes B and C, so data transformation will be carried out provided that if it works it changes to 1 and if it doesn't work it changes to 0. Transformation result dataset is shown in Table 1.

Table 1. Transformation Result Dataset

No	Name	A	B	C	D	E	Target
1	A1	0	1	0	Rp6.000.000	Rp182.000	Worthy
2	A2	5	1	1	Rp2.600.000	Rp362.000	Worthy
…	...	…	…	…	…	…	…
76	A76	5	1	0	Rp2.400.000	Rp5.210.000	Worthy
77	A77	3	1	1	Rp2.400.000	Rp790.000	Worthy

Next, data normalization was carried out using (1) to produce Table 2.

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Table 2. Preprocessing Result Dataset

No	Name	A	B	C	D	E	Target
1	A1	0,0000	1,0000	0,0000	1,0000	0,0349	Worthy
2	A2	0,6250	1,0000	1,0000	0,4333	0,0695	Worthy
…	...	…	…	…	…	…	…
76	A76	0,6250	1,0000	0,0000	0,4000	1,0000	Worthy
77	A77	0,3750	1,0000	1,0000	0,4000	0,1516	Worthy

The third stage is the implementation of KNN which consists of dividing the dataset into 80% training dataset and 20% testing dataset, that is consecutively 61 and 16. The percentage distribution of this dataset is based on research conducted by Amelia & Aprianti (2023). The implementation results using KNN which were declared feasible amounted to 15 data and are presented in Table 3.

Table 3. The Result Dataset using KNN

No	Name	A	B	C	D	E
1	A57	0,5	1	0	0,4167	0,0864
2	A64	0,375	0	1	0,0021	0,0188
…	...	…	…	…	…	…
14	A76	0,6250	1,0000	0,0000	0,4000	1,0000
15	A77	0,3750	1,0000	1,0000	0,4000	0,1516

The steps for applying AHP-TOPSIS in determining mustahik are described as follows.

1. The criteria used in SPK are the same as the attributes used in KNN implementation.
2. The pairwise comparison matrix between criteria is presented in the form of a matrix.
   a. Calculation example for r_{11}, r_{12}, r_{13}, r_{14}, and r_{15} using (2):

$$r_{11} = \frac{a_{11}}{\sum_{j=1}^{5} a_{ij}} = \frac{1}{1 + 0,5 + 1 + 5 + 4} = 0,0870$$

$$r_{12} = \frac{a_{12}}{\sum_{j=1}^{5} a_{ij}} = \frac{2}{2 + 1 + 1 + 4 + 2} = 0,2000$$

$$r_{13} = \frac{a_{13}}{\sum_{j=1}^{5} a_{ij}} = \frac{3}{2 + 1 + 1 + 4 + 2} = 0,2000$$

$$r_{14} = \frac{a_{14}}{\sum_{j=1}^{5} a_{ij}} = \frac{0,2}{0,2 + 0,25 + 0,25 + 2 + 0,33} = 0,0984$$

$$r_{15} = \frac{a_{15}}{\sum_{j=1}^{5} a_{ij}} = \frac{0,25}{0,25 + 0,5 + 0,5 + 3 + 1} = 0,0476$$

The R matrix is obtained in the same way and is presented in Table 4.

Table 4. Normalized Comparison Matrix

	A	**B**	**C**	**D**	**E**
A	0,0870	0,2000	0,2000	0,0984	0,0476
B	0,0435	0,1000	0,1000	0,1230	0,0952
C	0,0870	0,1000	0,1000	0,1230	0,0952
D	0,4348	0,4000	0,4000	0,4918	0,5714
E	0,3478	0,2000	0,2000	0,1639	0,1905

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b. Calculating weight values (eigenvectors) using (3)

$$Weight_A = \frac{\sum_{j=1}^{5} a_{1j}}{5} = \frac{0{,}0870 + 0{,}2000 + 0{,}2000 + 0{,}0984 + 0{,}0476}{5} = 0{,}1266$$

$$Weight_B = \frac{\sum_{j=1}^{5} a_{2j}}{5} = \frac{0{,}0435 + 0{,}1000 + 0{,}1000 + 0{,}1230 + 0{,}0952}{5} = 0{,}0923$$

$$Weight_C = \frac{\sum_{j=1}^{5} a_{3j}}{5} = \frac{0{,}0870 + 0{,}1000 + 0{,}1000 + 0{,}1230 + 0{,}0952}{5} = 0{,}1010$$

$$Weight_D = \frac{\sum_{j=1}^{5} a_{4j}}{5} = \frac{0{,}4348 + 0.4000 + 0.4000 + 0.4918 + 0.5714}{5} = 0{,}4596$$

$$Weight_E = \frac{\sum_{j=1}^{5} a_{5j}}{5} = \frac{0{,}3478 + 0{,}2000 + 0{,}2000 + 0{,}1639 + 0.1905}{5} = 0{,}2204$$

c. The calculation results λ_{max} using (4) is presented in Table 5.

Table 5. Lambda Calculation Result

	$A \times Weight_A$	$B \times Weight_B$	$C \times Weight_C$	$D \times Weight_D$	$E \times Weight_E$	Sum	$\frac{Sum}{Weight}$	λ_{max}
A	0,1266	0,1847	0,2021	0,0919	0,0551	0,6603	5,2165	5,4149
B	0,0633	0,0923	0,1010	0,1149	0,1102	0,4818	5,2178	
C	0,1266	0,0923	0,1010	0,1149	0,1102	0,5451	5,3952	
D	0,6329	0,3693	0,4041	0,4596	0,6613	2,5273	5,4989	
E	0,5063	0,1847	0,2021	0,1532	0,2204	1,2667	5,7461	

$$CI = \frac{5{,}4149 - 5}{5 - 1} = 0{,}1037$$

$$CR = \frac{0{,}1037}{1{,}12} = 0{,}0926$$

Because CR value is less than 10%, then the comparison of criteria weights is declared consistent, so that$weight = \{0{,}1266; 0{,}0923; 0{,}1010; 0{,}4596; 0{,}2204\}$.

3. Creates a normalized matrix from matrices X using (7).
   Calculation example for r_{11}, r_{12}, r_{13}, r_{14}, and r_{15} using (7):

$$r_{11} = \frac{x_{11}}{\sqrt{\sum_{i=1}^{15} x_{i1}^2}} = \frac{0{,}5}{\sqrt{0{,}5^2 + 0{,}375^2 + 0{,}5^2 + \cdots + 0{,}375^2}} = 0{,}2604$$

$$r_{12} = \frac{x_{12}}{\sqrt{\sum_{i=1}^{15} x_{i2}^2}} = \frac{1}{\sqrt{1^2 + 0^2 + 1^2 + \cdots + 1^2}} = 0{,}3333$$

$$r_{13} = \frac{x_{13}}{\sqrt{\sum_{i=1}^{15} x_{i3}^2}} = \frac{0}{\sqrt{0^2 + 1^2 + 1^2 + \cdots + 1^2}} = 0$$

$$r_{14} = \frac{x_{14}}{\sqrt{\sum_{i=1}^{15} x_{i4}^2}} = \frac{0{,}4167}{\sqrt{0{,}4167^2 + 0{,}0021^2 + 0{,}1083^2 + \cdots + 0{,}4^2}} = 0{,}2799$$

$$r_{15} = \frac{x_{15}}{\sqrt{\sum_{i=1}^{15} x_{i4}^2}} = \frac{0{,}0864}{\sqrt{0{,}0864^2 + 0{,}0188^2 + 0{,}0413^2 + \cdots + 0{,}1516^2}} = 0{,}0753$$

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The normalized decision matrix is obtained in the same way and is presented in Table 6.

Table 6. Normalized Decision Matrix

No	Name	A	B	C	D	E
1	A57	0,2604	0,3333	0,0000	0,2799	0,0753
2	A64	0,1953	0,0000	0,3536	0,0014	0,0164
3	A65	0,2604	0,3333	0,3536	0,0727	0,0360
4	A66	0,2604	0,0000	0,3536	0,1120	0,0670
5	A67	0,3255	0,3333	0,3536	0,1791	0,0335
6	A68	0,1302	0,3333	0,0000	0,1679	0,0468
7	A69	0,0000	0,0000	0,0000	0,0672	0,0000
8	A70	0,0000	0,0000	0,0000	0,3358	0,0000
9	A71	0,2604	0,3333	0,3536	0,6045	0,2192
10	A72	0,0651	0,0000	0,0000	0,0056	0,1021
11	A73	0,4557	0,3333	0,3536	0,2687	0,3372
12	A74	0,3255	0,3333	0,0000	0,2687	0,1589
13	A75	0,3255	0,0000	0,3536	0,2687	0,0996
14	A76	0,3255	0,3333	0,0000	0,2687	0,8719
15	A77	0,1953	0,3333	0,3536	0,2687	0,1322

4. Making a weighted normalized decision matrix using (8) produces Table 7.

Table 7. Weighted Normalized Decision Matrix

No	Name	A	B	C	D	E
1	A57	0,0330	0,0308	0,0000	0,1286	0,0166
2	A64	0,0247	0,0000	0,0357	0,0006	0,0036
3	A65	0,0330	0,0308	0,0357	0,0334	0,0079
4	A66	0,0330	0,0000	0,0357	0,0515	0,0148
5	A67	0,0412	0,0308	0,0357	0,0823	0,0074
6	A68	0,0165	0,0308	0,0000	0,0772	0,0103
7	A69	0,0000	0,0000	0,0000	0,0309	0,0000
8	A70	0,0000	0,0000	0,0000	0,1543	0,0000
9	A71	0,0330	0,0308	0,0357	0,2778	0,0483
10	A72	0,0082	0,0000	0,0000	0,0026	0,0225
11	A73	0,0577	0,0308	0,0357	0,1235	0,0743
12	A74	0,0412	0,0308	0,0000	0,1235	0,0350
13	A75	0,0412	0,0000	0,0357	0,1235	0,0219
14	A76	0,0412	0,0308	0,0000	0,1235	0,1922
15	A77	0,0247	0,0308	0,0357	0,1235	0,0291

5. Create a positive ideal solution using (9) and a negative solution using (10). Attributes A, B, C, and E are profit attributes, so that the positive ideal solution has maximum value and the negative ideal solution has minimum value. Meanwhile, attribute D is a cost attribute, so that the positive ideal solution has the minimum value and the negative ideal solution has the maximum value.

$$A^+ = (0{,}0577; 0{,}0308; 0{,}0357; 0{,}0006; 0{,}1922)$$
$$A^- = (0{,}0000; 0{,}0000; 0{,}0000; 0{,}2778; 0{,}0000)$$

6. Calculation example for S_1^+ using (11) and calculation example for S_1^- using (12)

$$S_1^+ = \sqrt{\sum_{j=1}^{5} (y_{1j} - y_j^+)^2}$$
$$= \sqrt{\begin{array}{c}(0{,}0330 - 0{,}0577)^2 + (0{,}0308 - 0{,}0308)^2 + (0{,}0000 - 0{,}0357)^2 \\ +(0{,}1286 - 0{,}0006)^2 + (0{,}0166 - 0{,}1922)^2\end{array}} = 0{,}2216$$
$$S_1^- = \sqrt{\sum_{j=1}^{5} (y_{1j} - y_j^-)^2}$$

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$$= \sqrt{\begin{matrix}(0{,}0330 - 0{,}0000)^2 + (0{,}0308 - 0{,}0000)^2 + (0{,}0000 - 0{,}0000)^2 \\ +(0{,}1286 - 0{,}2778)^2 + (0{,}0166 - 0{,}000)^2\end{matrix}} = 0{,}1567$$

The separation values of other alternatives are calculated using (11) and (12) in the same way to produce Table 8.

Table 8. Separation of Alternatives

No	Name	S+	S-
1	A57	0,2216	0,1567
2	A64	0,1939	0,2806
3	A65	0,1888	0,2512
4	A66	0,1887	0,2320
5	A67	0,2027	0,2054
6	A68	0,2047	0,2039
7	A69	0,2083	0,2469
8	A70	0,2571	0,1235
9	A71	0,3133	0,0751
10	A72	0,1829	0,2763
11	A73	0,1702	0,1868
12	A74	0,2033	0,1664
13	A75	0,2128	0,1652
14	A76	0,1290	0,2518
15	A77	0,2068	0,1658

7. Calculation example for C_1^+ using (13).

$$C_1^+ = \frac{S_1^-}{S_1^+ + S_1^-} = \frac{0{,}1567}{0{,}2216 + 0{,}1567} = 0{,}4143$$

The Relative Closeness Value to the Ideal Solution for each alternative is calculated using (13) in the same way to produce Table 9.

Table 9. The Relative Closeness Value to the Ideal Solution

No	Name	C_i^+	No	Name	C_i^+	No	Name	C_i^+
1	A57	0,4143	6	A68	0,4990	11	A73	0,5232
2	A64	0,5913	7	A69	0,5424	12	A74	0,4501
3	A65	0,5709	8	A70	0,3244	13	A75	0,4370
4	A66	0,5514	9	A71	0,1934	14	A76	0,6613
5	A67	0,5033	10	A72	0,6016	15	A77	0,4451

8. The ranking results based on the largest value to the smallest value are presented in Table 10.

Table 10. The Ranking Result

No	Name	C_i^+	No	Name	C_i^+	No	Name	C_i^+
1	A76	0,6613	6	A69	0,5424	11	A77	0,4451
2	A72	0,6016	7	A73	0,5232	12	A75	0,4370
3	A64	0,5913	8	A67	0,5033	13	A57	0,4143
4	A65	0,5709	9	A68	0,4990	14	A70	0,3244
5	A66	0,5514	10	A74	0,4501	15	A71	0,1934

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The system display that has been built using the PHP programming language is presented in Figure 2 to Figure 3.

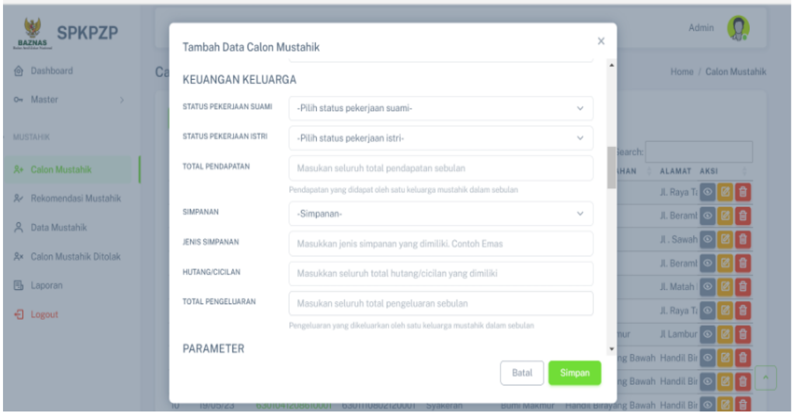

Figure 2. Display of The Page for Adding Mustahik Candidate Data

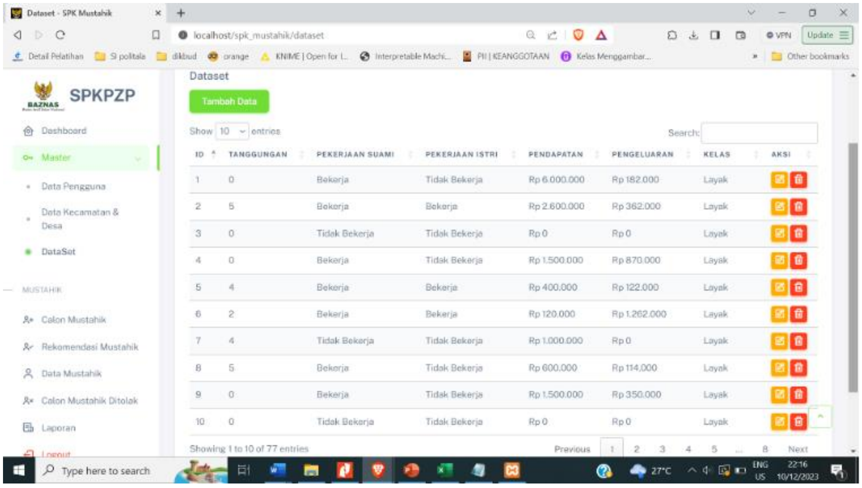

Fig.3 Dataset Page Display

DISCUSSION

Initial classification using KNN succeeded in classifying data on which mustahik candidates were preferred and which were not, thus helping to maximize the implementation of the SPK due to reduced alternatives. In SPK, determining the weight of criteria greatly influences the results of alternative ranking so that the application of AHP helps in determining the weight of mustahik selection. The weights are 12.66% for the number of dependents criteria, 9.23% for the husband's job criteria, 10.10% for the wife's job criteria, 45.96% for the total income criteria, and 22.04% for the total expenses criteria. The application of TOPSIS in ranking mustahik alternatives has been shown in Table 10 and helps in providing a recommendation system. If the funds distributed are for 5 mustahik, then based on the table the 10 selected are A76, A72, A64, A65, and A66. A recommendation system using the PHP programming language has been successfully built. Testing the functionality of the system with a black box has shown success in each of its features, including user data, mustahik candidate data, mustahik recommendations using KNN and AHP-TOPSIS, mustahik data, rejected mustahik candidate data, and reports. It is hoped that this system can help in decision making in selecting mustahik.

CONCLUSION

The criteria used in determining whether or not a mustahik candidate is eligible are the number of dependents, husband's job, wife's job, total income, total expenses, and the acceptance status of the mustahik candidate. The mustahik selection recommendation system built in this research includes the implementation of KNN to classify the eligibility of mustahik candidates, determining the weight of each criterion using AHP, and ranking alternatives using TOPSIS. The weights resulting from the AHP for each criterion are 12.66%, 9.23%, 10.10%, 45.96%, and 22.04%, respectively. This weight is used to determine the ranking of mustahik candidates. The application of TOPSIS resulted in the 76th candidate being ranked first in mustahik. In future research, we will compare KNN and AHP-TOPSIS with other classification methods and decision support systems to find methods with better performance.

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