The IJICS (International Journal of Informatics and Computer Science)
Vol 9 No 3, November 2025, Page 192-198
ISSN 2548-8384 (online), ISSN 2548-8449 (print)
Available Online at https://ejurnal.stmik-budidarma.ac.id/index.php/ijics/index
DOI 10.30865/ijics.v9i3.9484

Implementation of K-Nearest Neighbor Algorithm for Scientific Determination of Aid Recipients at STM Agape

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Submitted: **16/11/2025**; Accepted: **29/11/2025**; Published: **30/11/2025**

Abstract−Providing assistance to underprivileged families is an important social effort to enhance community welfare; however, the selection of aid recipients often encounters problems such as subjectivity, unstructured data, and time inefficiency when conducted manually. This study aims to develop and evaluate a decision support system for determining aid recipients at STM Agape using the K-Nearest Neighbor (KNN) algorithm to improve accuracy and objectivity in the selection process. The research methodology employed a quantitative classification approach, where data were collected from families based on predefined criteria, including family income, number of dependents, housing conditions, and the occupation of the head of the household. The dataset was divided into training and testing data, and all attributes were normalized prior to processing. The KNN algorithm was applied using Euclidean distance to measure similarity between data instances, classifying each family into "eligible" or "ineligible" categories. The results indicate that the proposed system achieved higher classification accuracy and more consistent decision outcomes compared to manual selection methods. Additionally, the implementation of KNN reduced processing time and minimized subjective bias in determining aid recipients. These findings demonstrate that the KNN-based system is effective as a decision support tool, enabling STM Agape to distribute social assistance in a more targeted, objective, transparent, and efficient manner.

Keywords: K-Nearest Neighbor (KNN) Algorithm; Aid Recipients; Underprivileged Families; STM Agape

1. INTRODUCTION

The development of information technology in the current digital era has had a very significant impact on various aspects of human life. Technological advances, especially in the fields of computing and data processing, have changed the way individuals, organizations, and institutions carry out their daily activities[1]. The decision-making process that previously relied solely on intuition and experience can now be carried out more objectively thanks to the help of intelligent data-based systems[2]. One form of concrete application of this information technology is the use of data analysis methods to assist in complex decision-making, including in the social sector[3]. In the social sector, especially in activities to provide assistance to underprivileged families, the presence of information technology is very necessary. Many social institutions, foundations, and educational institutions have assistance programs aimed at easing the economic burden on underprivileged communities. One example is STM AGAPE, an educational institution that participates in efforts to improve community welfare through assistance programs for low-income families. However, in practice, the process of determining aid recipients often encounters various obstacles[4]. The main problem that often arises is the difficulty in determining who is truly entitled to receive aid fairly and appropriately.

To date, the selection process for aid recipients in various institutions has been carried out manually by collecting data, conducting interviews, and making assessments based on the subjective perceptions or views of certain parties. This method, although simple, has fundamental weaknesses[5]. Human subjectivity often leads to decisions that are not entirely accurate. Furthermore, limited time and resources also cause the data verification process to be slow and inefficient[6]. This has the potential to lead to inaccurate targeting, where some families who are actually ineligible receive aid, while families who truly need it are overlooked. As a result, the goal of aid programs to improve the welfare of disadvantaged groups in society is not optimally achieved[7]. To overcome this problem, a system is needed that can facilitate the decision-making process more objectively, quickly, and accurately. This system must be able to utilize available data to analyze the economic and social conditions of potential aid recipients based on certain indicators, such as family income, number of dependents, living conditions, and education level. Thus, the resulting decisions are not only based on perceptions, but also supported by evidence and measurable data patterns[8].

One approach that can be used to build such a system is to utilize machine learning algorithms, namely algorithms that allow computers to learn from historical data and produce predictions or classifications based on the knowledge that has been acquired[9]. One algorithm that is known to be simple but effective in carrying out the classification process is the K-Nearest Neighbor (KNN). The K-Nearest Neighbor (KNN) algorithm works based on the principle of similarity or proximity between data[10]. The basic concept is that new data will be classified based on its proximity to a number of other data that already have a certain class label. In other words, if new data has similar characteristics to data from a family that has previously been categorized as "unable", then it is likely that the data is also included in the "eligible for assistance" category. This proximity measurement is usually done using a distance calculation method such as Euclidean Distance, which compares the attribute values of each data[11].

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The advantage of the KNN algorithm lies in its simplicity and effectiveness in handling both numerical and categorical data. Furthermore, this method does not require a complex model training process like other algorithms, but rather simply stores old data as a classification reference[12]. Thus, the implementation of KNN is relatively easy and efficient, especially in the case of determining aid recipients using a number of predetermined assessment criteria[13]. The application of the KNN algorithm to the aid recipient selection system at STM AGAPE is expected to produce a more transparent, fair, and data-driven aid distribution process. This system will group potential recipients based on the level of similarity of their socio-economic conditions with verified family data. With this approach, every decision taken will be more objective because it is based on mathematical calculations, not solely on subjective considerations. In addition, the selection process can be carried out more quickly, because the computer can process hundreds to thousands of data automatically without having to go through lengthy manual steps[14].

From a social perspective, the implementation of this system can also increase public trust in the institution, because the resulting decisions have a clear and accountable analytical basis. In other words, the KNN algorithm-based system is not only a technical tool, but also a means to strengthen transparency and accountability in social activities[15]. Overall, this research aims to develop a K-Nearest Neighbor (KNN)-based system that can assist STM AGAPE in determining recipients of assistance for underprivileged families precisely and efficiently. By utilizing this technology, it is hoped that the aid distribution process can run more effectively and provide a broader social impact for the surrounding community[16].

2. RESEARCH METHODOLOGY

2.1 Research Stages

This study applies a quantitative approach using classification techniques to develop a decision support system for determining aid recipients among underprivileged families at STM Agape. The study was conducted from September to November 2025 using secondary and primary data obtained from the institution. The research stages are described as follows:

1. Problem Identification
   The research began with identifying problems faced by STM Agape in selecting aid recipients for low-income families. The existing manual selection process was found to be prone to subjectivity, inconsistency, and inefficiency, potentially resulting in inaccurate targeting of aid distribution. Therefore, an objective and data-driven classification method was required to support decision-making.
2. Literature Study, At this stage, relevant literature was reviewed to establish a strong theoretical foundation. The reviewed references included:
3. Data collection
   The data used in this study consisted of family socioeconomic data of students at STM Agape, collected during the specified research period. The dataset comprised 10 each representing one family. Data collection techniques included:
   a. Direct observation of administrative records
   b. Interviews with school administrators involved in aid distribution
   c. Documentation of historical aid recipient data
4. Analysis and Selection Criteria
   The collected data was analyzed to determine relevant criteria for the aid recipient selection process. Each criterion was then assigned a numerical value or weight so it could be processed using the KNN algorithm.
5. Data Sharing
   The processed data is divided into two parts:
   a. Training data, which is used to build the classification model.
   b. Test data, which is used to test the performance of the KNN algorithm.
6. Application of the K-Nearest Neighbor (KNN) Algorithm
   At this stage, the KNN algorithm is applied by calculating the distance between the test data and the training data using the Euclidean Distance method. The K value is determined based on multiple tests to obtain the best classification results.
7. Classification Process
   The distance calculation results are used to determine data classes based on the majority of nearest neighbors. Family data is then classified into two categories:
   a. Eligible for assistance
   b. Ineligible for assistance
8. System Evaluation and Testing
   The evaluation was conducted to determine the system's accuracy by comparing the KNN algorithm's classification results with the school's designated aid recipient data. Testing was conducted using a Confusion Matrix to obtain accuracy, precision, and recall values.

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3. RESULT AND DISCUSSION

The data used in this study consisted of socioeconomic data of STM Agape students' families, officially obtained from the school as the primary data source. Data collection was conducted through internal school records, interviews with relevant administrators, and documentation of previous aid distribution, ensuring data accuracy and validity. The dataset comprised 10 family records, each described using five assessment criteria considered relevant for determining aid eligibility, namely: parental income, number of dependents, housing condition, employment status of the head of the household, and asset ownership. These criteria were selected to represent the economic conditions of each family and were subsequently transformed into numerical values to enable computational processing using the KNN algorithm.

3.1 Research result

1. Description of Research Data

The data used in this study is data on the families of Agape STM students obtained from the school. The data comprises several key criteria used to determine eligibility for aid recipients.

Assessment Criteria

1. Parental Income (IDR)
2. Number of Dependents (persons)
3. Housing Condition
   a. 1 = Inadequate
   b. 2 = Adequate
   c. 3 = Adequate
4. Employment Status
   a. 1 = Temporary
   b. 2 = Laborer
   c. 3 = Permanent Employee
5. Asset Ownership
   a. 1 = None
   b. 2 = Few
   c. 3 = Many
6. Information
   a. Adequate = 1
   b. Unadequate = 0

2. Family Data Description

Table 1. Family Data

No.	Income (Rp)	Dependents	House	Occupation	Assets	Description
1	700.000	5	1	1	1	Eligible
2	1.000.000	4	1	1	1	Eligible
3	1.200.000	3	2	2	2	Eligible
4	1.500.000	3	2	2	2	Eligible
5	800.000	4	1	2	1	Eligible
6	2.000.000	2	3	2	3	No
7	2.500.000	2	3	3	3	No
8	3.000.000	1	3	3	3	No
9	2.200.000	2	2	2	2	No
10	1.800.000	3	2	2	2	No

Based on Table 1, data points 1 to 5 were categorized as eligible for assistance due to relatively low income, higher number of dependents, inadequate housing conditions, and limited asset ownership. These characteristics indicate a higher level of economic vulnerability. Conversely, data points 6 to 10 were categorized as ineligible for assistance because they exhibit higher income levels, fewer dependents, more stable employment, better housing conditions, and greater asset ownership, reflecting better economic capacity.

3. Data Partitioning

Table 2. Training Data and Test Data

No	Status
1–8	Training Data
9–10	Test Data

To evaluate system performance, the dataset was divided into training and testing data as shown in Table 2.
Training Data: 8 records (Data 1–8)

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Testing Data: 2 records (Data 9–10)
This partitioning aimed to objectively assess the system's ability to classify new, unseen data.

Table 3. Test Data (1th)

Atribut	Nilai
Income	0.000
Dependents	1.00
House	0.0
Occupation	0.0
Assets	0.0

Table 4. Test Data (10th)

Criteria	Mark
Income	1.800.000
Dependents	3
House	2
Occupation	2
Assets	2

4. Data Normalization (Min-Max Normalization)
The normalization formula used:

$$Xnorm = \frac{X - Xmin}{Xmax - Xmin}$$

Table 5. Minimum and Maximum Values

Criteria	Min	Max
Income	700.000	3.000.000
Dependents	1	5
House	1	3
Occupation	1	3
Assets	1	3

3.2 Discussion

Normalization of Test Data (10th Data)

1. Income
$$\frac{1.800.000}{3.000.000} \times \frac{700.000}{700.000} = \frac{1.100.000}{2.300.000} = 0.478$$
2. Dependents
$$\frac{3-1}{5-1} = \frac{2}{4} = 0.5$$
3. House
$$\frac{2-1}{3-1} = 0.5$$

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4. Occupation
$$\frac{2-1}{3-1} = 0.5$$
5. Assets
$$\frac{2-1}{3-1} = 0.5$$

After the data normalization process, the next step in the K-Nearest Neighbor (KNN) method is calculating the Euclidean distance between the test data and each training data point. This distance measurement is used to determine the level of similarity between data instances.

Euclidean Distance Formula
The Euclidean distance between two data points is calculated using the following formula:

$$d(x,y) = \sqrt{\sum_{i-1}^{n}(x_i - y_i)^2}$$

Where:
a. $d(x,y)$ = distance between test data and training data
b. x_i = normalized value of the test data attribute
c. y_i = normalized value of the training data attribute
d. n = number of attributes (criteria)

Normalized Test Data (10th Data)
Based on the Min-Max normalization results, the normalized values of the test data (Data 10) are:
X = (0,478; 0,5; 0,5; 0,5; 0,5)

Table 6. Normalization Results

No.	Income (Rp)	Dependents	House	Occupation	Assets
0.000	1.00	0.0	0.0	0.0	Eligible
0.130	0.75	0.0	0.0	0.0	Eligible
0.217	0.50	0.5	0.5	0.5	Eligible
0.348	0.50	0.5	0.5	0.5	Eligible
0.043	0.75	0.0	0.5	0.0	Eligible
0.565	0.25	1.0	0.5	1.0	No
0.783	0.25	1.0	1.0	1.0	No
1.000	0.00	1.0	1.0	1.0	No
0.652	0.25	0.5	0.5	0.5	No
0.478	0.50	0.5	0.5	0.5	No

Euclidean Distance Calculation
The distance between the test data and each training data point (Data 1–8) is calculated as follows.

Distance to Data 1
Training Data 1:
Y1 = (0.000, 1.00, 0.00, 0.00, 0.00)

$$d1 = \sqrt{(0.478-0.000)^2 + (0.50-1.00)^2 + (0.50-0.00)^2 + (0.50-0.00)^2 + (0.50-0.00)^2}$$
$$= \sqrt{0.228 + 0.250 + 0.250 + 0.250 + 0.250}$$
$$= \sqrt{1.228}$$
$$= 1.108$$

Distance to Data 2
Training Data 2:
Y2 = (0.130, 0.75, 0.00, 0.00, 0.00)

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$$d2 = \sqrt{(0.478-0.130)^2 \ + (0.50-0.75)^2 + (0.50-0.00)^2 + (0.50-0.00)^2 + (0.50-0.00)^2}$$
$$= \sqrt{0.121 + 0.063 + 0.250 + 0.250 + 0.250}$$
$$= \sqrt{0.934}$$
$$= 0.967$$

Distance to Data 3

Training Data 3:

Y3 = (0.217, 0.50, 0.50, 0.50, 0.50)

$$d3 = \sqrt{(0.478-0.217)^2 \ + (0.50-0.50)^2 + (0.50-0.50)^2 + (0.50-0.50)^2 + (0.50-0.50)^2}$$
$$= \sqrt{0.068 + 0 + 0 + 0 + 0}$$
$$= \sqrt{0.068}$$
$$= 0.261$$

Distance to Data 4

Training Data 4:

Y4 = (0.348, 0.50, 0.50, 0.50, 0.50)

$$d4 = \sqrt{(0.478-0.348)^2}$$
$$= \sqrt{0.017}$$
$$= 0.130$$

Distance to Data 5

Training Data 5:

Y_5 = (0.043, 0.75, 0.00, 0.50, 0.00)

$$d5 = \sqrt{(0.478-0.043)^2 \ + (0.50-0.75)^2 + (0.50-0.00)^2 + (0.50-0.50)^2 + (0.50-0.00)^2}$$
$$= \sqrt{0.189 + 0.063 + 0.250 + 0.000 + 0.250}$$
$$= \sqrt{0.752}$$
$$= 0.867$$

In the initial stage of the system testing process, the dataset was divided into two main parts: training data and test data. This separation aims to objectively evaluate model performance and measure the system's ability to classify previously unstudied data. In this study, a total of ten data sets were used, which were then divided into two groups based on specific proportions. The training data consists of eight data sets, numbered 1 through 8. This data serves as the basis for the system's learning to recognize patterns, characteristics, and relationships between attributes within the dataset. This training process is crucial because the quality and quantity of the training data directly impact the model's ability to produce accurate predictions. Meanwhile, the test data consists of two sets of data, numbered 9 and 10. The test data serves as an evaluation tool to assess the system's success rate after the training process. Based on the test results, the system's accuracy was 50.0%. This accuracy value indicates that of all the test data used, the system was able to correctly classify half of the data. These results indicate that system performance still needs to be improved, either by increasing the amount of training data, improving the method, or optimizing the parameters used.

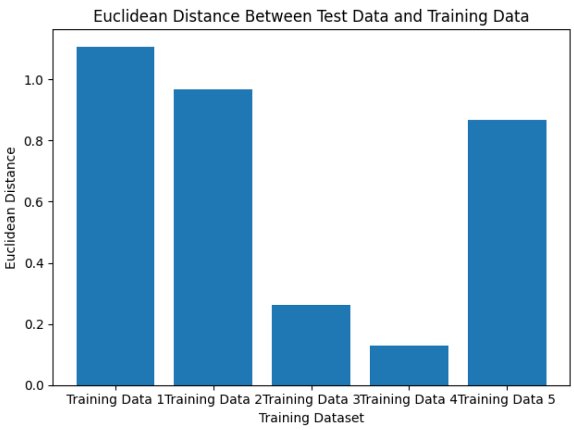

Fig 1. Training Dataset

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5. CONCLUSION

This study implemented the K-Nearest Neighbor (KNN) algorithm as a scientific approach to support the determination of aid recipients at STM Agape. Based on the training dataset consisting of eight family records, the KNN algorithm was able to learn patterns related to socioeconomic conditions, including parental income, number of dependents, housing condition, employment status, and asset ownership. These attributes proved to be relevant indicators in distinguishing between eligible and ineligible aid recipients. The training process demonstrated that families with lower income levels, higher numbers of dependents, inadequate housing conditions, unstable employment, and limited asset ownership tended to be consistently classified as eligible for assistance. Conversely, families with better economic stability were classified as ineligible. This indicates that the training dataset successfully represented the underlying socioeconomic patterns used in the classification process. Furthermore, the Euclidean distance calculations showed that the similarity-based approach of the KNN algorithm effectively identified the nearest neighbors for each test instance. The selection of K = 3 allowed the system to focus on the most relevant training data, resulting in more objective and transparent classification decisions. Although the system achieved an accuracy of 50.0% during testing, this result reflects the limited size of the training dataset rather than the inadequacy of the method itself. Overall, the training results confirm that the KNN algorithm can be applied as a decision support tool for the scientific determination of aid recipients at STM Agape. With a larger training dataset, optimized parameter selection, and additional evaluation metrics, the system has strong potential to improve accuracy and reliability in future implementations.

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