PT. Keberlanjutan Strategis Indonesia

Letter of Acceptance

14 of August 2025

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Article Title: Analysis of Machine Learning Utilization in Identifying Social Assistance Recipients in Aceh Province

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https://journalkeberlanjutan.com/index.php/jtep
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	ANALYSIS OF MACHINE LEARNING UTILIZATION IN IDENTIFYING SOCIAL ASSISTANCE RECIPIENTS IN ACEH PROVINCE
Volume: 3 Number: 1 Page: 01 - 07	**Rajul Hakim[1], Muhammad Adnan[2], Winny Dian Safitri[3]** [1,2,3]Universitas Islam Negeri Ar-Raniry Banda Aceh, Indonesia Corresponding author: Rajul Hakim E-mail: 210604065@student.ar-raniry.ac.id
Article History: Received: YY-MM-DD Revised: YY-MM-DD Accepted: YY-MM-DD	**Abstract:** Poverty is still an ongoing problem in Indonesia, especially in Aceh Province, even though various interventions such as the Program Keluarga Harapan (PKH) and the use of the Kartu Keluarga Sejahtera (KKS) have been implemented. This study aims to classify social assistance recipients more accurately, in order to reduce poverty levels in Aceh Province. This study uses secondary data from the 2023 National Socio-Economic Survey (Susenas) with a total of 13,316 household observations and involving 28 independent variables. The results of the study show that the Classification Tree algorithm is able to classify households with an accuracy rate of 80%. The most influential variables in predicting KKS recipients include the education of the head of the household, floor area, number of household members, source of drinking water, and employment status. These findings indicate that a data-driven approach can improve the targeting accuracy of social assistance programs and support poverty alleviation efforts more effectively.
	Keywords: Machine Learning, Social Assistance, Prosperous Family Card

INTRODUCTION

Poverty is not only a long-standing, unresolved problem but also a reflection of social inequality that remains evident in various parts of the world, including Indonesia. This phenomenon describes a condition in which individuals or groups live in limitations, unable to meet basic needs such as food, shelter, education, and adequate access to healthcare (Ministry of Finance of the Republic of Indonesia, 2023). The perspective of poverty encompasses the same basic rights. Poverty is not only viewed in terms of economic inability but also encompasses the neglect of various basic rights and the disparate treatment of individuals or groups who should be able to live with dignity (Hasyim et al., 2023). The problem of poverty is persistent and an issue in Indonesian society.

Aceh Province, with all its natural and historical riches, still faces significant challenges in terms of poverty. Although known as a region rich in natural resources, Aceh has not been able to fully eradicate the poverty problem that shackles the majority of its citizens. Based on data (Central Statistics Agency, 2024), the percentage of the poor population in Aceh Province decreased from 14.45% in March 2023 to 14.23% in March 2024. Furthermore, data on the number of poor people in Aceh in March 2024, which was 804,530 thousand people, decreased by 2.22 thousand people compared to the poor population in March 2023, which was 806.75 thousand people. Aceh Province now has the highest percentage of poor people on the island of Sumatra, along with the increasing number of people living below the poverty line. It shows that poverty in Aceh is not just an economic problem, but is also related to social and cultural factors and the impact of the prolonged conflict that has plagued this region.

One solution implemented by the government to alleviate poverty in Aceh Province is the Program Keluarga Harapan(PKH), with the Prosperous Family Card (KKS) as one of its main instruments. This program is designed to provide conditional social assistance to poor and

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vulnerable families registered at the village office, with the aim of improving welfare and fulfilling basic needs such as education, health, and nutrition. This program is part of the acceleration of poverty alleviation as regulated in Presidential Regulation (Perpres) Number 166 of 2014. To ensure better and more efficient program distribution, this program also requires the use of technology to reach underprivileged communities.

The Family Kartu Keluarga Sejahtera(KKS) is a non-cash assistance program in the form of savings provided to low-income families. Launched in February 2017, the government initially provided Rp 1.32 million per year or Rp 110,000 per month to 15.6 million families. In 2019, the assistance value increased to Rp 1.8 million per year or Rp 150,000 per month, and during the COVID-19 pandemic, it was increased again to Rp 2.4 million per year or Rp 200,000 per month for 20 million families. The KKS program is valid for five years and can be terminated if the recipient's economic condition improves. However, recipient selection is often challenging due to the numerous criteria that must be met to ensure the assistance is properly targeted. Accurate tools are essential to classify who is and is not eligible to receive the KKS program.

Various studies have demonstrated the use of machine learning methods in predicting the eligibility of social assistance recipients, such as the Program Keluarga Harapan(PKH). Research by Aribowo et al. (2021) explains that the CART algorithm was used to classify PKH recipients in Ngarejo Village with three outcomes: Eligible, Considered, and Not Eligible. This algorithm is capable of generating decision trees that are used to test new data in determining aid recipients. Meanwhile, Nuzula et al. (2020) conducted a classification analysis of poor households in Wonosobo Regency using two methods: SVM and CART. The results showed that the SVM method had a higher accuracy (89.94%) than CART (89.31%), but both methods were less effective in predicting the minority class, although they performed well in the majority class.

Furthermore, this study also included a Graphical User Interface (GUI) that validated the classification results. Research by Nur et al. (2024) compared the Naive Bayes and C4.5 algorithms in predicting the eligibility of PKH recipients. The results show that Naive Bayes has the highest accuracy (99.87%) with an AUC of 1,000, which is categorized as an excellent classification, superior to C4.5, which only achieved an accuracy of 99.61% with an AUC of 0.743, which is categorized as a fair classification. These results indicate that Naive Bayes is more effective in predicting the eligibility of social assistance recipients, making it a superior method compared to other algorithms, including CART and C4.5, especially in handling prediction accuracy in minority categories. However, in displaying impotent variables, CART is quite representative and provides good exploration.

One classification method that can be used to identify these differences in characteristics is the Classification Tree method. A Classification Tree is a machine learning method whose output is easy to understand and analyze, and conclusions are easily drawn. The novelty of this paper lies in the proposed use of the Classification Tree method to identify important variables in identifying social assistance recipients in Aceh Province. This machine learning-based approach offers an innovative solution to address classic challenges in poverty alleviation. This study aims to classify social assistance recipients more accurately, in order to reduce poverty levels in Aceh Province, So that in distributing aid it is on target and there is no error in processing who is eligible to receive assistance. This can reduce poverty through accuracy in distributing the recommended aid from the day of classification.

METHODS

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The data used in this study is secondary data obtained from the Central Statistics Agency (BPS), which includes the results of the March 2023 National Social and Economic Survey (SUSENAS) in Aceh Province. The data in this study consist of 13,316 observations, with the unit of observation being households. The study used 29 variables: 28 independent variables and one dependent variable, namely recipients of Community Empowerment Program (KKS) assistance, divided into two categories: recipients and non-recipients. Data analysis in this study consisted of descriptive and inferential analysis using Python software.

Table 1. Variable Details

Variable	Variable Definition	Information
Y	Prosperous Family Card Recipients (KKS)	0: Not a Recipient 1: Recipient
X_1	Residential Ownership Status	1: Owned 2: Contract/Lease 3: Service 4: Rent-Free
X_2	Floor Area	m^2
X_3	Types of Residential Roofs	1: Concrete 2: Roof Tiles 3: Zinc 4: Asbestos 5: Others
X_4	Types of Residential Floors	1: Marble/ceramic 2: Parquet/vinyl/carpet 3: Cement/red brick 4: Tile/terrazzo 5: Wood/plank 6: Other
X_5	Types of Residential Walls	1: Wall/plaster/wire 2: Wood/board 3: Other
X_6	Types of Residential Toilets	0: None 1: Gooseneck 2: Flap with lid 3: Flap without lid 4: Flap with lid
X_7	Types of Electricity Usage	1: Electricity 2: Not electricity
X_8	Cooking Fuel	1: 12 kg/5.5 kg LPG/Blue Gas 2: 3 kg LPG 3: Kerosene 4: Firewood 5: Others
X_9	Main Source of Drinking Water	1: Bottled/refillable water 2: Piped water 3: Borehole water 4: Spring/river/lake 5: Other

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X_{10}	Main Source of Water for Bathing/Washing/Etc.	1: Bottled/Refillable Water 2: Piped Water 3: Borehole Water 4: Spring/River/Lake Water 5: Other
X_{11}	Refrigerator Ownership	0: No 1: Yes
X_{12}	AC Ownership	0: No 1: Yes
X_{13}	Computer/Laptop Ownership	0: No 1: Yes
X_{14}	Gold/Jewelry Ownership (Min. 10 G)	0: No 1: Yes
X_{15}	Motorcycle Ownership	0: No 1: Yes
X_{16}	Car Ownership	0: No 1: Yes
X_{17}	TV Ownership (Min. 30 Inch)	0: No 1: Yes
X_{18}	Land Ownership	0: No 1: Yes
X_{19}	HP Ownership	0: No 1: Yes
X_{20}	Internet Access	0: No 1: Yes
X_{21}	Head of Household's Last Education	1: Did not complete elementary school 2: Elementary school/equivalent 3: Middle school/equivalent 4: High school/equivalent 5: College
X_{22}	Head of Household Employment Status	0: No 1: Yes
X_{23}	Number of Families	1: 1 family 2: 2 families 3: ≥ 3 families
X_{24}	Number of Household Members (ART)	1: 1 person 2: 2 people 3: 3 people 4: 4 people 5: ≥ 5 people
X_{25}	Number of Toddlers (0 – 4 Years)	1: None 2: 1 person 3: 2 people 4: ≥ 3 people
X_{26}	Number of household members aged 5 - 9 years	1: None 2: 1 person 3: 2 people 4: ≥ 3 people

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X_{27}	Number of household members aged 10 – 17 years	1: None 2: 1 person 3: 2 people 4: ≥ 3 people
X_{28}	Average Household Expenditure Per Capita Per Month	Rupiah

Machine Learning. Machine learning is a branch of artificial intelligence that encompasses various approaches that enable computers to learn tasks without being directly programmed (Sarker, 2021). Machine learning algorithms work by studying patterns embedded in data, commonly known as data mining, to generate information.

1. Data preprocessing is a crucial stage in the data mining process, aiming to prepare the data for further processing. This process includes several stages: data cleaning which consists of filtering data from Susenas micro data so that it gets a database that is ready to be analyzed, then data integration and transformation into categories is carried out in the data transformation process, and data reduction to check so that nothing is missing from the transformation data.
2. Data balancing in classification: when data is imbalanced, commonly used algorithms may consider minority observations as outliers and ignore them in the analysis, thus classifying the sample into the majority class. As a result, the prediction accuracy for the minority class will be significantly lower than for the majority class. To address this issue, imbalanced data classes must first be balanced. Synthetic Minority Over-sampling Technique (SMOTE) is a sample centering technique that is often used to overcome the problem of class imbalance in data. Data balancing was carried out in this study when before classification was carried out because the percentage of the number of aid recipients was smaller than the non-KKS assistance recipient category. In this study, it is divided into two data, namely training and testing with SMOTE to get a good exploration of important variables with a ratio of 30% training data and 70% testing data.

Classification and Regression Trees. One method for data mining is classification. This classification refers more to grouping using a binary decision tree model. One algorithm is CART (Classification and Regression Trees). According to (Yohannes & Hoddinott, 1999) and (Otok & Sumarni, 2009), the level of confidence that can be used in classifying new data in CART is the accuracy produced by a classification tree formed purely from data with similar conditions. The CART method provides a good interpretation by providing the result of impotent variables through the Cut-off value. CART recursively divides records in a data set into subsets of records with similar values for the target attribute (Larose & Larose, 2014). The steps of the CART algorithm are as follows:

1. Prepare the data to be classified.
2. Determine the predictor variables as the basis for grouping based on the objective (target) variable.
3. Determine the candidate left and right splits.
4. Measure the goodness (suitability) of each candidate branch s at decision node t which is calculated using the formula:

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$$\Phi(s|t) = 2P_L P_R \sum_{j=1}^{jlh\ kategori} |P(j|t_L) - P(j|t_R)$$

Description:
tL = candidate left branch of decision node t
tR = candidate right branch of decision node t
PL = number of records in the candidate left branch tL / total number of records
PR = number of records in candidate right branch tR / total number of records
P(j | tL) = number of records in category j in candidate left branch tL / total number of records in decision node t
P(j | tR) = number of records in category j in candidate left branch tR / total number of records in decision node t

5. Determine the candidate branch for the decision node by choosing the largest value; this branch is not calculated again.
6. Draw the decision node branches and termination event nodes.
7. Repeat step 4 until there are no more decision node branches.

RESULT AND DISCUSSION

General Overview of the Distribution of Households Receiving the Family Welfare Card (KKS) in Aceh Province. The Prosperous Family Card (KKS) program is a form of social assistance aimed at improving the welfare of Indonesians, particularly poor and vulnerable families. Data exploration revealed the distribution of households receiving the KKS in Aceh Province.

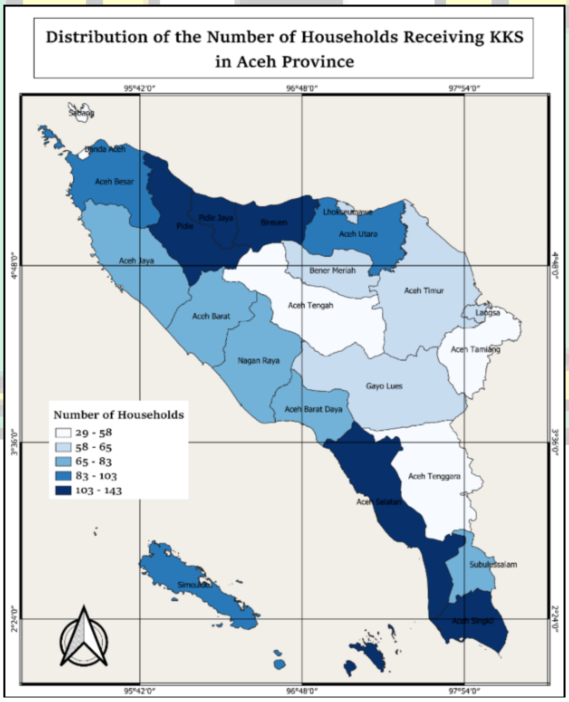

Figure 1. Distribution of the Number of Households Receiving KKS in Aceh Province

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Based on Figure 1, areas such as Sabang, Banda Aceh, Central Aceh, Aceh Tamiang, and Southeast Aceh had the fewest recipients, with between 29 and 58 households. Meanwhile, areas with the largest number of recipients, with between 103 and 143 households, were in South Aceh, Singkil, Pidie, Pidie Jaya, and Bireuen.

Results of Data Analysis of Social Assistance Recipients Using a Decision Tree. This analysis was conducted to classify households as recipients and non-recipients of social assistance (KKS) in Aceh Province. The model used was a Decision Tree, with performance evaluation based on metrics such as accuracy, precision, recall, and importance scores. The data consisted of two categories:

1. Category 0: Households not receiving KKS.
2. Category 1: Households receiving KKS.

The model evaluation results showed relatively high overall accuracy, but there was an imbalance in performance between the two categories. Details of the analysis results are shown in the following table:

Table 2. Results of KKS Social Assistance Analysis

	Precision	*Recall*	*F1-Score*	*Support*
0	0.88	0.89	0.89	2294
1	0.18	0.16	0.17	343
Accuracy			0.80	2637
Macro Avg	0.53	0.53	0.53	2637
Weighted Avg	0.79	0.80	0.79	2637

Table 2 shows the results of the analysis of the classification of KKS social assistance recipients using the Decision Tree method, indicating that the model has an accuracy rate of 80%. The model performed better in classifying the non-recipient category (0) than the recipient category (1). A precision of 0.18 for category 1 means that of all those predicted to be recipients, only 18% are actually recipients. A recall of 0.16 means that only 16% of the total actual recipients were successfully identified by the model. This suggests that the model still struggles in identifying the actual recipients of KKS, which is the main goal of this study. It is evident from the precision and accuracy values indicating the model was able to identify the majority of non-recipient households accurately. The importance score also emphasizes the performance imbalance, with a score of 89% for non-recipients. This imbalance is likely caused by the difference in data volume between the two categories, with the non-recipient category having a much larger amount of data. This is because SMOTE affects performance metrics, especially for minority classes, so the next step needs to be classified with the Boosting method for the continuation of this study.

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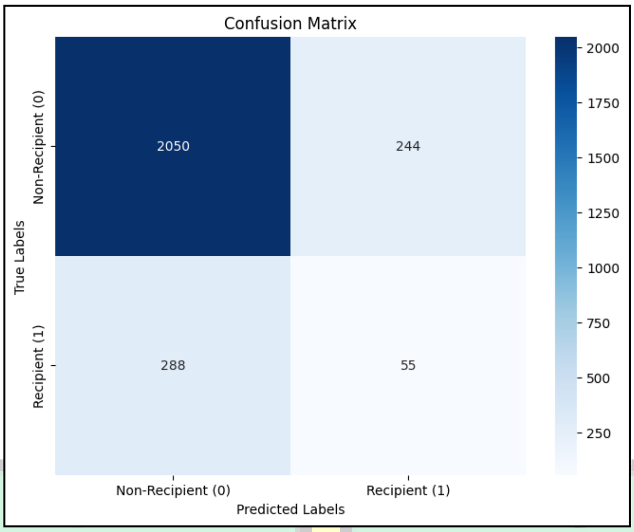

Figure 2. Results of Confusion Matrix Calculation

Based on Figure 2, it can be seen that 2,050 non-KKS recipient households are correctly classified as non-KKS recipient households. 244 non-KKS recipient households that are incorrectly classified as KKS recipient households, 288 KKS recipient households that are incorrectly classified as non-KKS recipient households, and 55 PKH recipient households that are correctly classified as KKS recipient households.

The method to determine the most influential variables in predicting households receiving KKS social assistance is to use the Feature Importance method from the Decision Tree classification model.

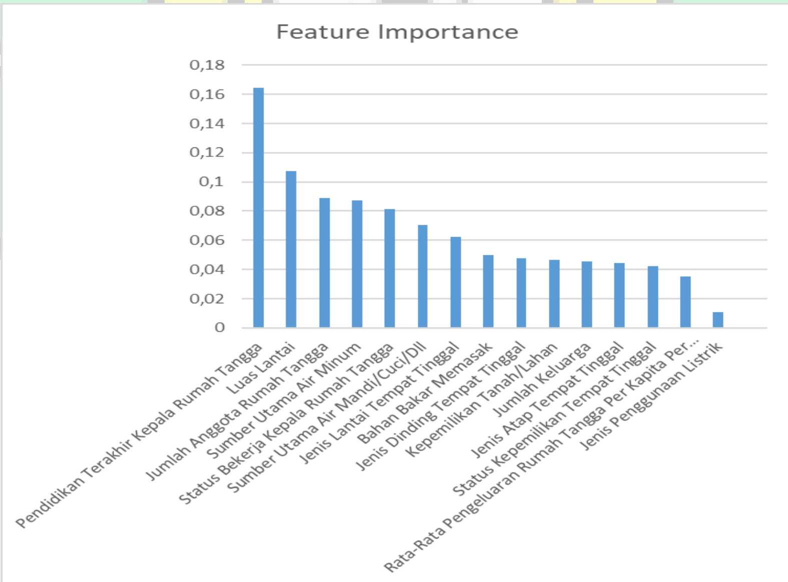

Figure 3. Order of Variable Contribution Based on the Decision Tree Classification Model

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Figure 3 shows that the variable value using the Feature Importance method from the Decision Tree Classification model with the highest value is the Head of Household's Last Education, which is 16%, followed by Floor Area of 11%, Number of Household Members of 9%, Main Source of Drinking Water of 9%, and Head of Household's Employment Status of 8%.

The variables of household head education, floor area category, and number of household members rank first, second, and third as the variables with the highest contribution in predicting households receiving KKS social assistance. It aligns with the results of research conducted by Agwil et al. (2022) on poverty classification in Bengkulu Province, which found that the most important variables determining poor households are the number of household members, the head of household's most recent diploma, and the house's floor area.

The drinking water source variable is another variable with a significant contribution in predicting households receiving the Family Welfare Card (KKS). It is supported by research conducted by Kustanto (2015) on the impact of drinking water sources and sanitation on improving welfare. According to him, drinking water sources influence life expectancy, which is an indicator of welfare. Another study conducted by Wulandari & Yeniwati (2023) examined the influence of employment on the chances of receiving the Family Welfare Card (KKS) in West Sumatra. Employment status has a positive and significant influence on recipients of the Family Welfare Card (KKS) in West Sumatra Province at a significance level of 5%. It means that the more heads of households work in the agricultural sector, the more households receive the Family Welfare Card (KKS) assistance.

CONCLUSION

Based on the analysis and discussion, this study demonstrates that machine learning methods, specifically the Decision Tree (CART) algorithm, can be effectively used to identify households receiving social assistance in Aceh Province. Using survey data from the 2023 National Social and Economic Survey (SUSENAS) and various household socio-economic variables, the model is able to identify important factors such as the education level of the head of the household, floor area, number of household members, drinking water source, and employment status as key indicators in determining eligibility for assistance. These results confirm that data-driven technology can support a more accurate and objective social assistance distribution process.

The use of machine learning in this context not only improves the efficiency of aid recipient identification but also has the potential to impact poverty reduction efforts significantly. By implementing a system that improves targeting accuracy, government programs such as the Prosperous Family Card (KKS) can be distributed to groups truly in need, thereby preventing aid leakage and increasing the effectiveness of social protection programs. In the long term, the application of this technology can provide a crucial foundation for local and central governments in formulating more adaptive, transparent, and evidence-based poverty alleviation policies.

This study has limitations in the performance of the model in minority classes and the potential for future improvement (e.g., by using other algorithms or more sophisticated balancing techniques) and more data. So for future research, such as the exploration of other algorithms, more balanced data collection, or the integration of other factors that may be relevant and using classification algorithms through SMOTE and data balancing.

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