

Application of the C5.0 Algorithm to Determine the Eligibility of BPJS Contribution Assistance Recipients in the National Health Insurance Program

Muhammad Furqan^{1*}, Nurdin², Rizki Suwanda¹

¹Department of Informatics, Faculty of Engineering, Universitas Malikussaleh, Aceh, Indonesia

²Department of Information Technology, Faculty of Engineering, Universitas Malikussaleh, Aceh, Indonesia

*Corresponding author Email: muhammad.200170173@mhs.unimal.ac.id

The manuscript was received on 8 August 2024, revised on 10 November 2024, and accepted on 15 March 2025, date of publication 11 April 2025

Abstract

The National Health Insurance (JKN) is a government program to provide health insurance to all Indonesian citizens. In its implementation, determining the eligibility of premium assistance recipients still faces challenges regarding accuracy and efficiency. This study aims to implement the C5.0 algorithm in classifying the eligibility of JKN premium assistance recipients and measure the accuracy of the resulting classification model. The method used is the C5.0 algorithm with the boosting technique with 10 trials and global pruning, with a 70:30 training and testing data split ratio, minimum cases of 2, and confidence level of 0.2. The research results show that the classification model performs excellently with an accuracy rate of 94.27%, precision of 83.78%, Recall of 90.29%, F1-Score of 86.92%, and AUC of 92.81%. The Specificity, reaching 95.34%, demonstrates the model's reliability in identifying ineligible participants for assistance. With a total algorithm execution time of 0.2224 seconds, these results indicate that the C5.0 algorithm can be implemented as an effective decision support system in determining the eligibility of JKN premium assistance recipients.

Keywords: Algorithm C5.0, Classification, Data Mining, Machine Learning, Premium Assistance.

1. Introduction

Healthcare as a fundamental right for the Indonesian population is affirmed in Law Number 40 of 2004 on the National Social Security System, which emphasizes the right of every individual to live prosperously both physically and mentally, to have a decent place to live and to obtain a healthy living environment, including healthcare services. This is in line with Article 28 H paragraph (1), which emphasizes the importance of such rights, and paragraph (3), which affirms the right of every person to social security for the comprehensive development of oneself as a dignified human being. Thus, fulfilling the right to health services becomes an integral part of the government's efforts to ensure the welfare and dignity of every individual in society[1].

One of the implementations of the National Social Security System (SJSN) is the National Health Insurance Program (JKN), which is managed by the Social Security Agency for Health (BPJS Kesehatan). This program, which has been in effect since 2014, uses a social insurance mechanism and mandates participation for all Indonesian residents. There are two segments of participants in the JKN: the Contribution Assistance Recipients (PBI) and non-PBI participants. The central and regional governments cover the financing of contributions for PBI participants, while for non-PBI participants, the contributions are paid by employers, workers, or individual by individuals[2].

Based on the decision of the Minister of Social Affairs of the Republic of Indonesia number 73/HUK/2024 regarding the procedures for data proposal and verification and validation of the Integrated Social Welfare Data (DTKS), the data proposal process can be submitted through village or sub-district deliberations or other names, which will then be registered into the Integrated Social Welfare Data to be forwarded to BPJS Kesehatan to become PBI participants. Determining the eligibility of the community members who will receive the contribution assistance is still done manually through village deliberations. This causes difficulties for the village in determining whether the community members who wish to become PBI participants are eligible to be subsequently registered with BPJS Kesehatan.

The impact of the development of information technology is very significant for daily life, and one of its benefits is that it assists in activities that require a high level of precision[3]. Effective decision-making through information systems relies on operational data and



requires data analysis to uncover potential information. The rapid development of globalization in the internet world encompasses various sectors, bringing many changes, including to specific industries. This advancement not only changes the way individuals interact but also affects the way information is obtained[4]. Meanwhile, according to [5], classification is a technique used to build a classification model from training data samples. Classification will analyze the input data and create a model that will describe the class of that data. The class label of an unknown data sample can be predicted using classification techniques.

C5.0 is the commercial version of the C4.5 algorithm, widely used in various data mining software, such as Clementine and RuleQuest. Although C4.5 is widely known, the proper use of algorithms in C5.0 has not yet been fully revealed in the literature. Several studies indicate that C5.0 is more efficient in terms of memory usage, with savings of around 90%, and offers higher speed compared to C4.5. The C5.0 algorithm is one of the methods in data mining classification that relies on decision tree techniques and is considered an advanced development of the previous algorithms developed by Ross Quinlan in 1987, namely ID3 and C4.5[6].

The C5.0 algorithm can generate decision trees or a set of rules due to classification. One of the main advantages of this algorithm is its ability to handle data containing diverse values while requiring a relatively short time to learn. C5.0 is a classifier that can classify data more efficiently than other classifiers. The main focus of using decision trees is minimal memory and increased accuracy. C5.0 is an improvement of the C4.5 algorithm, where C5.0 addresses several weaknesses of C4.5, such as better classification results, lower error rates, higher prediction accuracy, more efficient time usage, and more economical memory usage[7].

The C5.0 algorithm is an advanced development of the ID3 and C4.5 algorithms. In creating a decision tree, this algorithm selects the attribute with the highest information gain value to serve as the root of the next node. The process begins by considering all the data as the root of the decision tree; then, the selected attribute will be used to split the data samples. The same entropy formula used in the C4.5 algorithm is applied to calculate the attribute size, while the formula from the C4.5 algorithm is used to obtain the information gain value. The attribute with the highest information gain will be chosen as the root node. The C5.0 algorithm is known for its high Accuracy, ability to handle various types of data, and its advantage in processing large volumes of data, making it very practical for use in different data mining applications [8] [9].

From the explanation presented, the research on applying the C5.0 algorithm in determining the eligibility of PBI BPJS participants in the National Health Insurance Program (JKN) becomes meaningful and relevant because the C5.0 algorithm has significant advantages in processing categorical data for classification. The ability of this algorithm to produce efficient classification models with high Accuracy has been proven through various studies, including its application in social assistance programs such as the Family Hope Program (PKH) and the determination of scholarship recipients. The advantages of the C5.0 algorithm, such as higher Accuracy, time efficiency, and minimal memory usage, make it an appropriate method to be applied in the process of determining the eligibility of participants in the Contribution Assistance Recipients (PBI) program under the National Health Insurance Program (JKN). By applying the C5.0 algorithm, it is expected that the classification process can be carried out more accurately, effectively, and transparently, thereby supporting the optimization of the social security system in Indonesia [10].

2. Literature Review

2.1. National Health Insurance Program

Based on Law No. 40 of 2004 concerning the National Social Security System (Law SJSN), it can be formulated that JKN is a social security program that guarantees health maintenance costs and the fulfilment of basic health needs, organized nationally on a mandatory cooperation basis by all Indonesian citizens by paying periodic contributions or having their contributions paid by the government to the non-profit health social security organizer, namely BPJS Kesehatan[11]. Participation in BPJS Health is divided into three categories: first, the independent BPJS participants, referred to as individual BPJS participants, whose monthly contributions are borne personally; second, the Wage Recipient Workers BPJS (PPU), specifically for workers in a company who receive wages with part of their monthly premium covered by the company they work for; and third, the Contribution Assistance Recipients BPJS (PBI), designated for people experiencing poverty who meet the criteria set by the social services, with their monthly contributions paid by the government and regulated by the government. Of the three categories, the most participants are the BPJS PBI participants [12] [13].

2.2. Information System

Information systems consist of various interconnected components, primarily generating information in a specific field[14]. Information Systems can also play a role in the decision-making process. This includes a combination of individuals, hardware, software, computer networks, data communication, and databases in collecting, disseminating, and transforming information within an organization[15].

2.2.1 Visual Studio Code (VS CODE)

Visual Studio Code is a source code editor developed by Microsoft for Windows, Linux, and macOS. Visual Code makes writing code that supports several programming languages easier and provides colour variations according to the function in the code sequence. Another feature is the ability to add extensions, which developers can add to enhance features unavailable in Visual Studio Code [16] [17].

2.2.2 Hypertext Preprocessor (PHP)

PHP stands for Hypertext Preprocessor, a high-level scripting language used in HTML documents. The syntax of PHP is mainly similar to C, Java, and Perl, but it has some special functions. The primary purpose of PHP is to enable the creation of dynamic and automatically functioning websites [18].

2.2.3 XAMPP

XAMPP is an open-source application for managing servers developed by Apache Friends. This application can be used for free because it is open-source. The name XAMPP reflects cross-platform support, allowing it to run on various operating systems such as Windows, macOS, and Linux. XAMPP consists of Apache, MariaDB (a development of MySQL), PHP, and Perl. This application provides a simple, lightweight solution for creating a local web server for website testing. XAMPP can be run on Mac and Linux [19].

2.3. Classification

Classification is a method for determining a model that emphasizes or clarifies the differences between concepts or data classes. Classification also becomes one of the models in data mining that functions to find a model to differentiate data classes with the aim of unknown classes. The classification model is developed using training data. The application of this model is also used to test the accuracy of the classification rules against the testing data used [20].

2.4. Decision Tree (DT)

Decision tree (DT) is one of the methods frequently used in various fields, such as machine learning, image processing, and pattern recognition. DT is a sequential model that efficiently combines a series of basic tests, where numerical features are compared against threshold values in each test. Conceptual rules are much easier to create than numerical weights in neural networks connecting nodes. Moreover, DT is a commonly used classification model in data mining. Nodes and branches consist of each tree; each node represents a feature in the category to be classified, and each subset defines the values that can be taken by that node [21].

2.5. C5.0 Algorithm

The C5.0 algorithm is a classification algorithm used in data mining, particularly in decision tree techniques. This algorithm is an extension of two previous algorithms created by Ross Quinlan in 1987, namely ID3 and C4.5. The process of tree formation in the C5.0 algorithm is almost the same as in the C4.5 algorithm, especially in the calculation of entropy and information gain. However, the main difference lies in the subsequent steps after calculating the information gain. In the C4.5 algorithm, the calculation stops after computing the information gain, whereas in the C5.0 algorithm, the next step is to calculate the gain ratio[22]. The C5.0 algorithm was chosen because of its good performance in generating information on rules based on nodes produced through gain and entropy calculations[23].

Formula to find the value of entropy :

$$Entropy (S) = \sum_{i=1}^n -P_i \times \log_2 P_i \quad (1)$$

Explanation:

S: Case Set

n: Number of Partitions S / Number of Classes

Pi: The proportion of Si to S

$$Formula to find the value of information gain : \dots \quad (2)$$

$$InformationGain(S, A) = Entropy (S) - \sum_{i=1}^n \frac{|S_i|}{|S|} \times Entropy (S_i)$$

Explanation:

S: Case Set

A: Attribute

n: Number of Partitions on attribute A

| Si |: Number of cases in partition i

| S |: Number of cases in S

Formula to find the gain ratio:

$$Gain Ratio = \frac{InformationGain(S, A)}{\sum_{i=1}^n Entropy (S_i)} \quad (3)$$

2.6. Confusion Matrix

Confusion matrix is an evaluation method that uses a matrix table. This matrix consists of several cells, each containing a number indicating the number of test data classified correctly and the number of test data misclassified. The confusion matrix table is as follows:

Table 1. Confusion Matrix

Actual	Prediction	
	Class +	Class -
Class +	TP (True Positive)	FN (False Negative)
Class -	FP (False Positive)	TN (True Negative)

Where TP is the number of positive data correctly classified by the system, TN is the number of negative data correctly classified by the system. FN is the number of positive data classified as negative by the system. FP is the number of negative data classified as positive by the system[24]. Here are the formulas to measure accuracy, F1-Score, precision, recall, specificity, Area Under Curve(AUC), and sensitivity based on the confusion matrix :

$$Accuracy (\%) = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (4)$$

$$Accuracy (\%) = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (5)$$

$$F1 - Score (\%) = \frac{2 \times (Precision \times Recall)}{Precision+Recall} \times 100\% \quad (6)$$

$$Precision (\%) = \frac{TP}{TP+FP} \times 100\% \quad (6)$$

..... (7)

$$Recall (\%) = \frac{TP}{TP+FN} \times 100\% \quad \dots \quad (8)$$

$$Specificity (\%) = \frac{TN}{TN+FP} \times 100\% \quad (9)$$

$$AUC (\%) = \left(\frac{(TPR + TNR)}{2} \right) \times 100\% \quad (10)$$

$$Sensitivity (\%) = \frac{TP}{TP+FN} \times 100\% \quad (10)$$

3. Research Method

3.1. Place and Time of Research

The research will be conducted in Langsa, specifically at the Geuchik office of Alue Merbau Village, from June 2024 until completion. This research is undertaken offline, where data is obtained directly from the office to meet the research needs, and the data collected focuses solely on the community data in the village of Alue Merbau.

3.2. System Schema

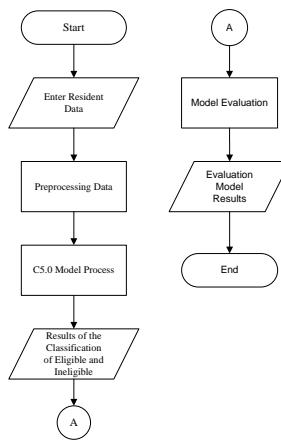


Fig 1. System Schema

The process of developing and evaluating the model with the C5.0 algorithm begins with inputting relevant population data, followed by data preprocessing, including handling missing data, splitting the dataset (80% training, 20% testing), and feature selection. The model is then trained using the training data to build a decision tree that generates classification rules. After training, the model is used to classify individuals into eligible or ineligible categories. Model evaluation is conducted using various metrics, such as confusion matrix, Accuracy, precision, Recall, F1-score, AUC, sensitivity, and Specificity, to ensure optimal performance. The final evaluation results provide a comprehensive overview of the model's Accuracy.

4. Result and Discussion

This research aims to apply the C5.0 algorithm in determining the eligibility of participants receiving contribution assistance (PBI) in the National Health Insurance (JKN) program. The system uses data from the community of Alue Merbau Village, which includes variables such as gender, age, family relationship, marital status, last education, occupation, and the number of dependents. This data was obtained from the Geuchik office of Alue Merbau Village, the primary information source. The main objective of this research is to explore the capabilities of the C5.0 algorithm in producing accurate and fair decisions regarding the eligibility of PBI recipients. With this approach, the research is expected to help develop a transparent and data-driven system, providing informative recommendations and supporting more effective decision-making. In addition, this research evaluates the performance of the C5.0 algorithm based on accuracy, reliability, and interpretation of classification results. The research results show that this method effectively identifies participant eligibility patterns based on predetermined criteria, providing a foundation for improving the quality of JKN program contribution assistance distribution in Alue Merbau Village.

4.1. Descriptive Data

Table 2. Variable Initialization

Variable Name	Variable Initial
Gender	X1
Age	X2
Family Relationships	X3
Marital status	X4

Last Education	X5
occupation	X6
Number of Dependents	X7

This research uses variable initialization to facilitate classification with the C5.0 algorithm in identifying the eligibility patterns of PBI recipients. The variables used include gender (X1), age (X2) in years, family relationship (X3) such as head of the family or child, marital status (X4) covering registered marriage or divorce, last education (X5) such as elementary school to university, occupation (X6) such as farmer or unemployed, and number of dependents (X7) which indicates family members who are dependents. With these variables, the analysis is more structured and objective to support targeted decision-making.

4.2. System Implementation

Fig 2. Analysis results page (Indonesia)

This Analysis Results page shows the details of the parameters used in the classification process with the C5.0 method. The parameters for splitting the training and testing data are set with a 70:30 ratio, which is the recommendation for large datasets. Following Ross Quinlan's recommendations, the minimum number of cases per node is set to 2, with a confidence level of 0.2. The boosting trials option is set to 10 trials, while the winnowing feature is disabled and global pruning is enabled. At the bottom of the page are execution times for each stage of the process. Data preparation takes 0.2866 seconds, while tree formation only takes 0.0219 seconds. The boosting process takes 0.0254 seconds, and pruning and evaluation require 0.0048 seconds and 0.0018 seconds, respectively. The total time needed for the entire classification process is 0.3405 seconds, indicating the system's efficiency in handling data. This data provides a clear picture of how fast and efficient the system performs classification analysis using the C5.0 method.

Fig 3. Training Data Table (Indonesia)

This table displays data divided into two parts: training data and testing data. Training data (70%) is used to train the model while testing data (30%) is used to test the accuracy of the trained model. Each row shows information about individuals, including the converted attribute values (X1 to X7) and the "Feasibility" classification results determined by the model. Users can see whether each individual in the training or testing data is classified as "Eligible" (marked in green) or "Not Eligible" (marked in red).

Data Testing (30%)									
NO	NAMA	X1	X2	X3	X4	X5	X6	X7	KELAYAKAN
1	MAHPIRA ZURA	2	20	3	3	5	3	0	TIDAK LAYAK
2	RIZKY AULIA	1	15	3	3	2	3	0	TIDAK LAYAK
3	RIZKY AZHAR	1	29	1	2	5	8	3	TIDAK LAYAK
4	ANITA SYAHFITRI	2	27	2	3	5	8	2	TIDAK LAYAK
5	REYHAN ALFARIQ GALINGGING	1	1	3	3	1	1	0	LAYAK
6	ZIDAN ALFAIRIZI GALINGGING	1	2	3	3	1	1	0	LAYAK
7	MUHAMMAD RIDHO NASUTION	1	26	1	2	5	8	1	TIDAK LAYAK
8	POPPY ANDRIANI	2	20	2	2	5	2	0	TIDAK LAYAK
9	AIYUB SRADEN	1	49	1	2	5	12	4	TIDAK LAYAK
10	WILDA WINITA	2	46	2	2	5	9	3	TIDAK LAYAK

Showing 1 to 10 of 489 entries

Previous 1 2 3 4 5 ... 49 Next

Fig 4. Testing Data Table (Indonesia)

This table displays the testing data that has been previously divided. This data is used to test the model's performance after training. As in the training data, each row contains the converted attribute values and classification results based on the model. Users can check the classification results and compare whether the model's predictions match reality. Some entries show a classification result of "Eligible" (green), while others are categorized as "Not Eligible" (red). This data provides an overview of the model's ability to predict the correct class based on unseen data during training.

Hasil Perhitungan Information Gain				
ATRIBUT	ENTROPY	INFORMATION GAIN	SPLIT INFO	GAIN RATIO
0	0.9183	0.0000	0.0000	0.0000
1	0.9183	0.9183	1.5850	0.5794
2	0.9183	0.0000	0.0000	0.0000
3	0.9183	0.0000	0.0000	0.0000
4	0.9183	0.0000	0.0000	0.0000
5	0.9183	0.2516	0.9183	0.2740
6	0.9183	0.0000	0.0000	0.0000

© 2025, KLASIFIKASI PBI

Fig 5. Table of Gain Ratio Calculation Results (Indonesia)

This table presents the calculation results for the Gain Ratio used in the decision tree creation process. Here, users can see the values of Entropy, Information Gain, Split Info, and Gain Ratio for each attribute. The gain Ratio measures how much information is obtained from the data division based on a particular attribute. Higher gain values indicate attributes that are more informative in distinguishing classes. Among the tested attributes, only attributes X1 and X7 showed a significant gain, with attribute X1 having the highest Gain Ratio of 0.5794. This information helps determine which attributes are most relevant for the decision tree. These three tables provide a complete overview of how the data is processed, tested, and evaluated using the C5.0 method and how the relevant attributes are used in building an accurate decision tree.

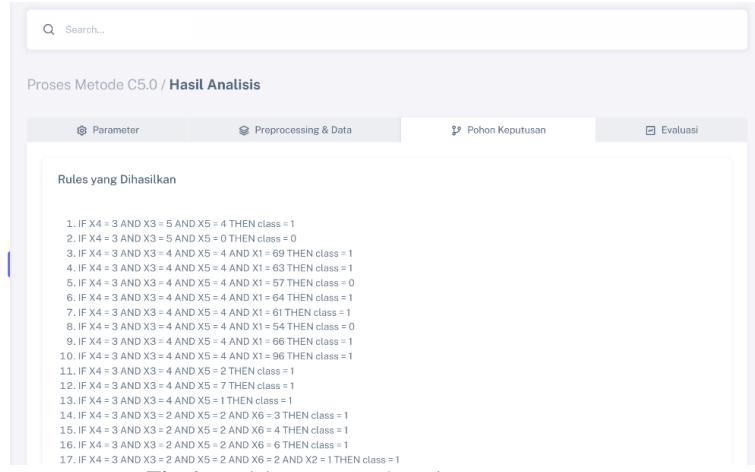


Fig 6. Decision Tree (Indonesia)

In this Decision Tree tab, the classification results are presented as rules generated by the C5.0 model. Each row displays a logical rule that connects the converted attributes with the classification result ("class"). For example, "IF X4 = 3 AND X3 = 5 AND X5 = 4 THEN class = 1" indicates that if the value of attribute X4 is 3, X3 is 5, and X5 is 4, then the class will be 1 (Eligible). These rules are used to classify new data based on the value of its attributes. Each rule breaks the data into smaller groups with more specific decisions, aiding the classification process. These rules are essential in explaining how the C5.0 model makes decisions and providing a deeper understanding of how particular attributes are interrelated in determining the class of a data point. With a considerable number of rules, this view demonstrates the complexity and strength of the model in performing analysis based on the given data.

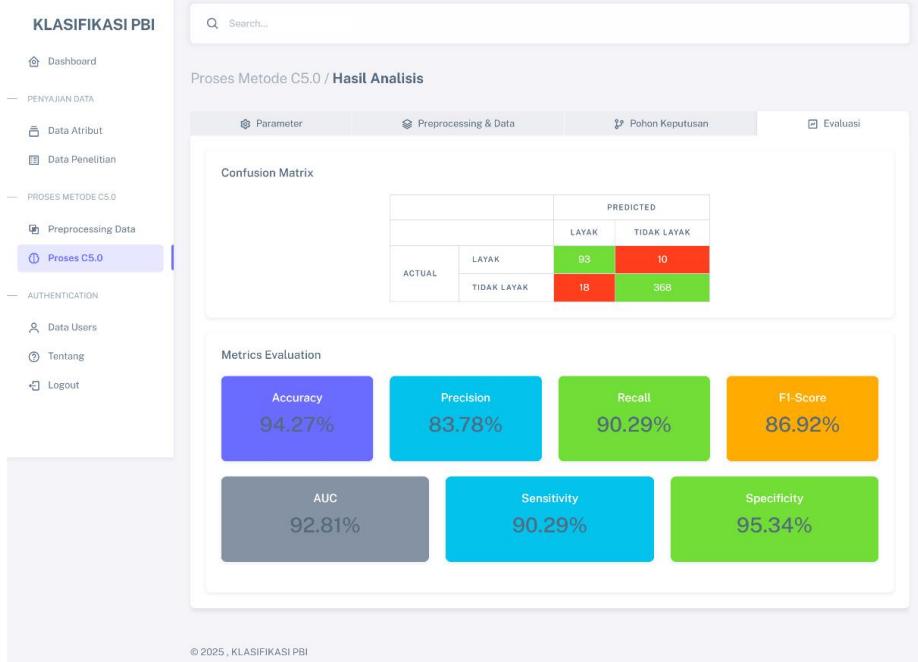


Fig 7. Confusion Matrix and Evaluation Metrics (Indonesia)

The evaluation results of the C5.0 model show excellent performance in classifying the data. Based on the Confusion matrix, the model accurately predicted 93 "Eligible" cases and 368 "Ineligible" cases. However, there were a few errors, with 18 "Ineligible" cases misclassified as "Eligible" and 10 "Eligible" cases predicted as "Ineligible." Other evaluation metrics, such as Accuracy, reached 94.27%, which means most of the model's predictions were correct. A precision of 83.78% indicates a good level of Accuracy in predicting the "Layak" class, while Recall at 90.29% shows that the model can capture most of the "Layak" cases. The F1-Score reaching 86.92% illustrates a solid balance between precision and Recall. An AUC of 92.81% indicates that the model can distinguish between the two classes well. Sensitivity and Specificity are at 90.29% and 95.34%, respectively, demonstrating the model's ability to detect both classes accurately. Overall, the C5.0 model shows excellent results in classifying "Eligible" and "Not Eligible" data with a relatively low error rate.

5. Conclusion

This study shows that implementing the C5.0 algorithm in determining the eligibility of BPJS JKN contribution assistance recipients has a very efficient computational performance with an execution time of 0.2224 seconds. The classification model achieved an accuracy of 94.27% from 489 test data, with 461 cases correctly classified (93 eligible and 368 ineligible), and a balanced performance evaluation with a precision of 90.29%, Recall of 83.78%, F1-Score of 86.92%, and AUC of 92.81%. This system effectively identifies ineligible participants (Specificity 95.34%) and eligible ones (sensitivity 83.78%), supporting the efficiency of the JKN budget. The boosting

technique (10 times) and global pruning with a minimum case parameter of 2 and a confidence level of 0.2 successfully optimized the model, supported by a 70:30 training-testing data ratio. These results prove that the C5.0 algorithm can be a reliable decision-making tool in determining the eligibility of BPJS JKN assistance recipients.

References

- [1] Husni Zelika and Hasim As’ari, “Implementasi Program Penerima Bantuan Iuran (Pbi) Jaminan Kesehatan Di Kota Pekanbaru,” *J. Hukum, Polit. Dan Ilmu Sos.*, vol. 1, no. 4, pp. 139–146, 2022, doi: 10.55606/jhps.v1i4.706.
- [2] B. Hidayat, “KEMAMPUAN MEMBAYAR IURAN JAMINAN KESEHATAN NASIONAL PESERTA PENERIMA BANTUAN IURAN (JKN PBI) KOTA TANGERANG TAHUN 2023,” vol. 8, no. 2, 2024.
- [3] Nurdin, M. Suhendri, Y. Afrilia, and Rizal, “Klasifikasi Karya Ilmiah (Tugas Akhir) Mahasiswa Menggunakan Metode Naive Bayes Classifier (NBC),” *Sistemasi*, vol. 10, no. 2, p. 268, 2021, doi: 10.32520/stmsi.v10i2.1193.
- [4] K. N. Ramdhani, Y. M. Sari, R. M. Nafi, A. Galvin, and F. Zahid, “Jurnal Computer Science and Information Technology (CoSciTech) Etika Web Developer dalam Pendistribusian Pop-Up Ads pada Website Web Developer Ethics in Distributing Pop-Up Ads on the Website,” vol. 5, no. 3, pp. 775–781, 2024.
- [5] R. Suwanda, Z. Syahputra, and E. M. Zamzami, “Analysis of Euclidean Distance and Manhattan Distance in the K-Means Algorithm for Variations Number of Centroid K,” *J. Phys. Conf. Ser.*, vol. 1566, no. 1, 2020, doi: 10.1088/1742-6596/1566/1/012058.
- [6] D. Fitrianah, W. Gunawan, and A. P. Sari, “Studi Komparasi Algoritma Klasifikasi C5.0, SVM dan Naive Bayes dengan Studi Kasus Prediksi Banjir,” *Techno.Com*, vol. 21, no. 1, pp. 1–11, 2022, doi: 10.33633/tc.v21i1.5348.
- [7] D. P. Utomo, P. Sirait, and R. Yunis, “Reduksi Atribut Pada Dataset Penyakit Jantung dan Klasifikasi Menggunakan Algoritma C5.0,” *J. Media Inform. Budidarma*, vol. 4, no. 4, pp. 994–1006, 2020, doi: 10.30865/mib.v4i4.2355.
- [8] M. Fajri, I. T. Utami, and M. Maruf, “Comparison of C4.5 and C5.0 Algorithm Classification Tree Models for Analysis of Factors Affecting Auction,” *Indones. J. Stat. Its Appl.*, vol. 6, no. 1, pp. 13–22, 2022, doi: 10.29244/ijsa.v6i1p13-22.
- [9] D. Irvansyah, C. I. Erliana, F. Fadlysyah, M. Ula, and M. Fahrizi, “Increasing Productivity in CPO Production Using The Objective Matrix Method,” *Int. J. Eng. Sci. Inf. Technol.*, vol. 2, no. 2, pp. 14–20, Jan. 2022, doi: 10.52088/ijesty.v2i2.232.
- [10] R. Aryanto, M. A. Rosid, and S. Busono, “Penerapan Deep Learning untuk Pengenalan Tulisan Tangan Bahasa Akasara Lota,” *J. Inf. dan Teknol.*, vol. 5, no. 1, pp. 258–264, 2023, doi: 10.37034/jidt.v5i1.313.
- [11] E. S. Sinaga, Ika Rahma Ginting, R. K. Kusumaratna, and T. Marthias, “Evaluasi Implementasi Program Jaminan Kesehatan Nasional (JKN) Di Provinsi DKI Jakarta, Indonesia,” *J. Kebijak. Kesehat. Indones. JKJI*, vol. 10, no. 03, pp. 1–9, 2021.
- [12] Rahmawati, “Prediction of the Number of Participants BPJS Recipient of Assistance Budget Using the Fuzzy Time Series Cheng Method,” *J. Ilmu Mat. dan Terap.*, vol. 15, no. 2, pp. 373–384, 2021.
- [13] S. Kumari and A. Harikrishnan, “Importance of Financial literacy For Sustainable Future Environment: A Research Among People In Rural Areas With Special Reference To Mandi District,Himachal Pradesh,” *Int. J. Eng. Sci. Inf. Technol.*, vol. 1, no. 1, 2021, doi: 10.52088/ijesty.v1i1.36.
- [14] M. Z. Prasetyo, E. Susanto, and A. Wantoro, “SISTEM INFORMASI REKAM MEDIS PASIEN THALASSEMIA (STUDI KASUS : POPTI Cabang BANDAR LAMPUNG),” *J. Teknol. Dan Sist. Inf.*, vol. 4, no. 3, pp. 349–355, 2023.
- [15] W. Darlin, A. D. Putra, and N. Hendrastuty, “Sistem Informasi Manajemen Kost Putra Trisula Berbasis Web (Studi Kasus: Asrama Putra Trisula),” *... dan Sist. Inf.*, vol. 4, no. 3, pp. 240–249, 2023.
- [16] N. Wilyanto, J. Firnando, B. Franko, S. P. Tanzil, H. C. Tan, and E. Hartati, “Pembuatan Website Menggunakan Visual Studio Code di SMA Xaverius 3 Palembang,” *Fordicate*, vol. 3, no. 1, pp. 1–8, 2023.
- [17] P. Sakinah, N. Hayati, and A. E. Syaputra, “Sistem Penunjang Keputusan Pemilihan Laptop Menggunakan Metode Simple Additive Weighting,” *J. Sistim Inf. dan Teknol.*, vol. 5, no. 2, pp. 130–138, Jul. 2023, doi: 10.37034/JSISFOTEK.V5I2.222.
- [18] Y. A. Sandria, M. R. A. Nurhayato, L. Ramadhani, R. S. Harefa, and A. Syahputra, “Penerapan Algoritma Selection Sort untuk Melakukan Pengurutan Data dalam Bahasa Pemrograman PHP,” *Hello World J. Ilmu Komput.*, vol. 1, no. 4, pp. 190–194, 2022, doi: 10.5621/helloworld.v1i4.187.
- [19] U. Kalsum Siregar, T. Arbaim Sitakar, S. Haramain, Z. Nur Salamah Lubis, U. Nadhirah, and F. Sains dan Teknologi, “Pengembangan database Management system menggunakan My SQL,” *SAINTEK J. Sains, Teknol. Komput.*, vol. 1, no. 1, pp. 8–12, 2024.
- [20] R. Widiyanti, C. Suhery, and R. Hidayati, “Implementasi Algoritma C5.0 Untuk Klasifikasi Kepuasan Masyarakat Terhadap Pelayanan Kantor Kecamatan,” *JURIKOM (Jurnal Ris. Komputer)*, vol. 9, no. 4, p. 1200, 2022, doi: 10.30865/jurikom.v9i4.4632.
- [21] B. Charbuty and A. Abdulazeez, “Classification Based on Decision Tree Algorithm for Machine Learning,” *J. Appl. Sci. Technol. Trends*, vol. 2, no. 01, pp. 20–28, 2021, doi: 10.38094/jast20165.
- [22] Y. A. Singgalen, “Penerapan Metode CRISP-DM dalam Klasifikasi Data Ulasan Pengunjung Danau Toba Menggunakan Algoritma Naïve Bayes Classifier (NBC) dan Decision Tree (DT),” *J. Media Inform. Budidarma*, vol. 7, no. 3, pp. 1551–1562, 2023, doi: 10.30865/mib.v7i3.6461.
- [23] I. Sahputra, M. Mauliza, and S. F. A. Zohra, “The Implementasi Algoritma C5.0 Pada Klasifikasi Status Gizi Ibu Hamil di Kota Lhokseumawe,” *Metik J.*, vol. 7, no. 1, pp. 42–46, 2023, doi: 10.47002/metik.v7i1.562.
- [24] R. N. Amalda, N. Millah, and I. Fitria, “Implementasi Algoritma C5.0 Dalam Menganalisa Kelayakan Penerima Keringanan Ukt Mahasiswa Itk,” *Teorema Teor. dan Ris. Mat.*, vol. 7, no. 1, p. 101, 2022, doi: 10.25157/teorema.v7i1.6692.