Implementation of the C4.5 Decision Tree Algorithm for Determining Dominant Factors in Village Welfare Based on Social and Infrastructure Indicators

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ABSTRACT
This study aims to identify the dominant factors influencing village welfare based on social and infrastructure indicators using the C4.5 Decision Tree algorithm. Conducted in Laut Tador Sub-district with data from the 2024 Prodeskel Kemendagri database, the study applies a quantitative data mining approach implemented in Python via Google Colaboratory. The classification analysis revealed that education and energy availability are the most dominant factors determining village welfare levels. The model achieved an accuracy of 100% and a gain ratio of 1.0, indicating strong reliability in classification performance. These findings demonstrate the potential of data-driven methods to support evidence-based rural policymaking, especially in identifying priority areas for improving village welfare.

Keywords : Decision Tree C4.5, Village Welfare, Social Indicators, Infrastructure Indicators, Data Mining.

INTODUCTION

Village development is a vital component of national progress aimed at enhancing the quality of life and reducing inequality in rural areas. Despite ongoing initiatives, many villages in developing countries still face disparities in access to basic services and infrastructure, resulting in uneven welfare levels. In Laut Tador Sub-district, for instance, several villages continue to struggle with poor road networks, limited health facilities, unequal access to education, and inadequate clean water sources. According to Prodeskel Kemendagri data (2024), only 40% of villages in the sub-district have proper health personnel, and less than half possess stable energy access. These conditions indicate that infrastructure and social disparities remain critical challenges affecting local welfare.

Previous studies have highlighted that economic growth, infrastructure, and social capital contribute to welfare improvement. However, most of these works are descriptive and rarely utilize computational methods capable of identifying dominant influencing factors. This gap limits policymakers' ability to design targeted strategies based on measurable evidence.

To address this gap, the present study applies the C4.5 Decision Tree algorithm to analyze social and infrastructure indicators of villages in Laut Tador. This method enables the classification of welfare levels and identification of the most influential attributes, combining analytical rigor with practical interpretability. The findings are expected to contribute to the development of data-driven rural policies by revealing the key determinants that most strongly influence village welfare.

LITERATUR REVIEW

Village welfare has been examined from various perspectives, including economic, infrastructural, and social dimensions. Several studies emphasize that infrastructure particularly roads, energy, and clean water plays a crucial role in improving access to education, health, and local markets. Improved road networks and clean water systems are associated with lower poverty and disease rates, ultimately strengthening local economies (Yunus, 2022; Suripto & Permatasari, 2023). However, both studies tend to focus on physical infrastructure alone, providing limited discussion on how it interacts with social dimensions of welfare, thus leaving a theoretical gap that this research seeks to address.

In terms of education, higher levels of education increase employment opportunities and citizen participation (Amelya & Marna, 2023), While other studies reinforce the role of education in improving economic and social welfare (Rahmadini et al., 2023). However, the study notes that most research on education is still descriptive and does not quantitatively model its interaction with other welfare indicators such as employment or health (Hasanah et al., 2023). This indicates that understanding well-being requires a more analytical and integrated approach that captures the reciprocal relationships between variables rather than analyzing them separately.

Employment patterns and livelihoods are also critical components in welfare analysis. Research has found that rural households that depend primarily on agriculture or the informal sector are highly vulnerable to economic shocks, while job diversification increases overall resilience and welfare (Rojia et al., 2023). Another study explains that employment is often considered a static indicator, ignoring its interaction with infrastructure or education (Nurhidayati, 2023).

Health infrastructure and access to medical services also play an important role in determining welfare outcomes. The availability of medical personnel and adequate facilities correlates with lower morbidity and higher productivity (Polgan et al., 2024). Adequate sanitation and clean water further strengthen health security. Yet, much of the Similarly, other studies have found that access to sanitation and clean water improves public health (Heryanto & Prayoga, 2023). However, both studies evaluated health variables separately, without integrating them with social or infrastructure dimensions. Therefore, a holistic computational framework can provide a clearer understanding of how health interacts with other determinants of welfare.

Social participation and institutional capacity also contribute to improved welfare. Active community involvement in decision-making strengthens local ownership of development outcomes (Maisyarah et al., 2023). While welfare mapping can reveal hidden inequalities between villages (Sari et al., 2023). However, these works remain descriptive and stop short of employing analytical or computational approaches, leaving space for models that can quantitatively capture the complexity of community dynamics.

The utilization of infrastructure continues to be a recurring theme in welfare research. Access to energy not only increases household productivity but also supports the quality of education and business activities, confirming energy as a key factor in improving (Octaningrum et al., 2025; Atifah et al., 2023). However, these studies do not systematically compare the contribution of energy relative to other indicators such as health or education, so the relative importance of energy remains unclear.

Recently, data-based approaches have begun to complement traditional welfare studies. In several case studies, it was reported that the C4.5 Decision Tree algorithm achieved high accuracy in social data classification (Nasution et al., 2024; Jannah et al., 2023).

While other studies highlighted the transparency and readability of the algorithm in decision making (Iddrus & Sari, 2023). However, other case studies have noted that this type of application is often limited to program evaluation or one-dimensional analysis (Yemi et al., 2024). In contrast to these studies, this study applies the C4.5 algorithm to simultaneously analyze social and infrastructure indicators, offering a more comprehensive perspective on welfare classification. Theoretically, welfare analysis is grounded in three key frameworks. Social Welfare Theory views welfare as multidimensional progress in community well-being, while Infrastructure-led Development Theory underscores the role of physical facilities in driving economic and social transformation. Complementing these, Social Capital Theory emphasizes trust, networks, and institutional collaboration as social assets that enhance welfare outcomes (Wadana & Prijanto, 2021; Tarigan et al., 2022). The integration of these theories provides a conceptual foundation for combining quantitative and computational analyses of welfare indicators.

Overall, prior studies acknowledge the importance of social and infrastructural factors but rarely analyze their combined effects using computational techniques. This study fills that gap by employing a data mining-based Decision Tree model to identify dominant welfare determinants, bridging theoretical understanding with empirical insights and contributing to evidence-based policymaking for sustainable rural development.

METHODS

This research was conducted in Laut Tador Subdistrict, which comprises ten villages serving as the analytical units. The study population consisted of village-level social and infrastructure data representing demographic, health, education, and basic facility conditions in each village. A purposive sampling technique was employed, selecting ten datasets obtained from the Prodeskel (Village and Subdistrict Profile) database of the Ministry of Home Affairs for the year 2024. These datasets included six key variables population, livelihoods, education, health personnel, clean water sources, and infrastructure facilities which were considered relevant for assessing village welfare.

Variable selection followed the indicator framework established by the Ministry of Home Affairs to ensure consistency and comparability across villages. The social indicators included population, occupation, education level, number of health workers, and access to clean water. Meanwhile, the infrastructure indicators consisted of energy sources, educational facilities (schools), health facilities, transportation access, and irrigation systems. Each indicator was classified into three categorical levels high, medium based on the value distribution across the ten villages. This classification aimed to simplify the construction of the decision tree and facilitate a clearer interpretation of the welfare determinants.

The data preprocessing stage was conducted to ensure data quality and readiness for analysis. This process included data cleaning by removing incomplete or duplicate entries, normalization to convert numerical attributes such as population and facility counts into categorical classes, and encoding to transform categorical values into label form suitable for algorithmic processing. The dataset was then divided into training and testing subsets for model validation purposes. All preprocessing and analysis procedures were performed using the Python programming language in Google Colaboratory, utilizing libraries such as Pandas, NumPy, and Scikit-learn for data manipulation and model construction.

The C4.5 Decision Tree algorithm was applied to classify village welfare levels based on the defined social and infrastructure indicators. The algorithm determines attribute importance through Information Gain and Gain Ratio, allowing for the identification of the most dominant variables influencing welfare. The resulting decision tree model visualized hierarchical decision rules that connect attribute combinations with welfare outcomes.

Model validation was carried out using the 10-fold cross-validation technique to assess the accuracy and generalization performance of the model. In this process, the dataset was divided into ten subsets, with nine used for training and one for testing, repeated iteratively until all subsets had been tested. Model performance was evaluated using accuracy, precision, recall, and F1-score metrics, as provided by Scikit-learn's metrics module. This validation approach ensured that the model results were robust and reliable.

Overall, the methodological framework of this study comprised five main stages: (1) data collection from the official Prodeskel Kemendagri database, (2) data preprocessing including cleaning, normalization, and encoding, (3) variable classification based on social and infrastructure indicators, (4) model construction using the C4.5 Decision Tree algorithm in Python, and (5) model validation and evaluation using 10-fold cross-validation and performance metrics. The overall workflow can be illustrated through the methodological flowchart below, which shows the sequential process from data collection to model evaluation in a structured and systematic manner.

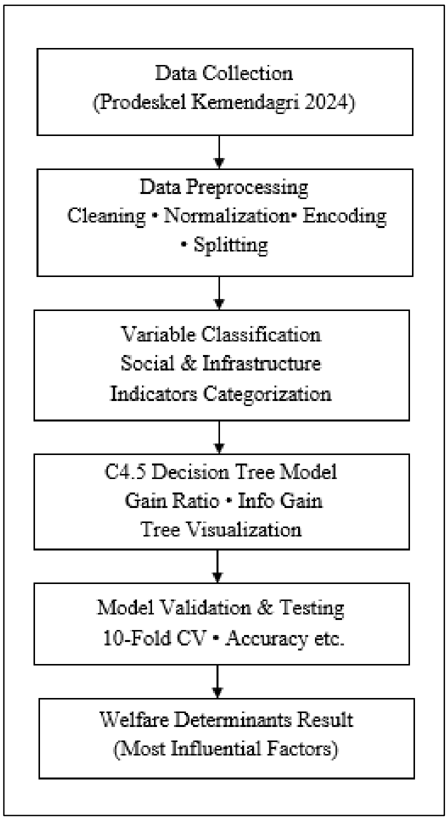

Figure 1. Methodological Flow Diagram of the Study

The methodological flow presented in Figure 1. summarizes the overall workflow of this study, starting from data collection to model evaluation. Each stage in the diagram represents a systematic step that ensures the accuracy and reliability of the final results. The subsequent sections explain each stage in more detail, beginning with the data preprocessing process and followed by variable classification, model construction using the C4.5 algorithm, and model validation.

RESULTS

The study analyzed both social and infrastructure indicators to identify the dominant factors influencing village welfare in Laut Tador Sub-district. Data preprocessing transformed numerical variables into categorical labels (medium and high) to enable classification analysis using the C4.5 Decision Tree algorithm. Two datasets were prepared one for social indicators and another for infrastructure indicators. The processed dataset for social indicators included population, livelihoods, health personnel, education, and clean water access. Villages were classified into welfare levels based on these indicators. A summarized visualization of this classification is shown in Figure 2, replacing the full table to simplify interpretation.

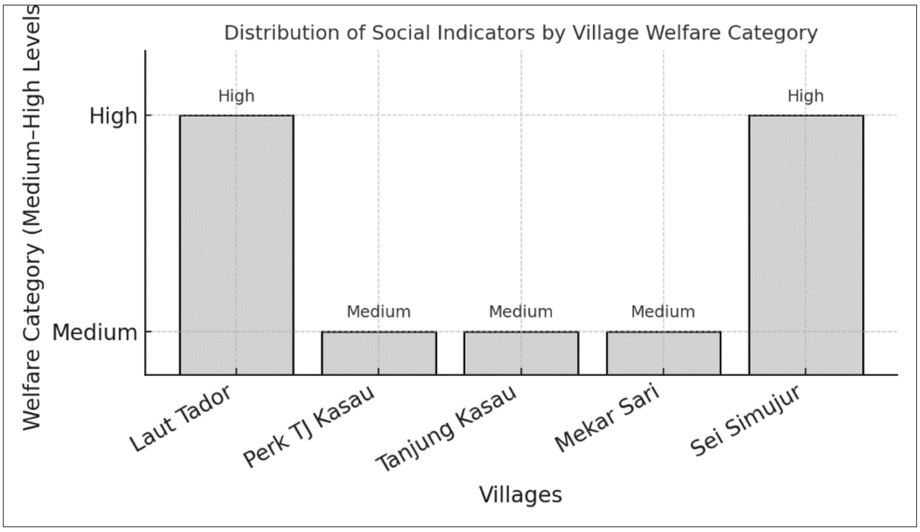

Figure 2. Distribution of Social Indicators

The Decision Tree results showed that education was the most dominant factor in determining welfare levels among social variables. Villages with higher education attainment generally achieved better welfare classifications, supported by secondary attributes such as health personnel and clean water access. The resulting model is visualized in Table 1.

Table 1. Attribute Importance of Social Indicators (C4.5)

Atribut	Criteria	Total (S)	Medium	High	Entropy	Gain	Split Info	Gain Ratio
Total	-	5	3	2	0.970951	-	-	-
Population	Medium	3	2	1	0.918296	0.42	0.971	0.433
	High	2	1	1	1	-	-	-
Livelihood	Medium	1	1	0	0	0.171	0.722	0.237
	High	4	2	2	1	-	-	-
Medical Personnel	Medium	1	1	0	0	0.171	0.722	0.237
	High	4	2	2	1	-	-	-
Water Sources	Medium	2	1	1	1	0.02	0.971	0.021
	High	3	2	1	0.918296	-	-	-
Education	Medium	2	0	2	0	0.971	0.971	1
	High	3	3	0	0	-	-	-

The decision tree visualization for social indicators was constructed to illustrate how attributes interact in the classification process. The model highlights the pathway of decisions leading to different welfare categories. The resulting tree is shown in Figure 2

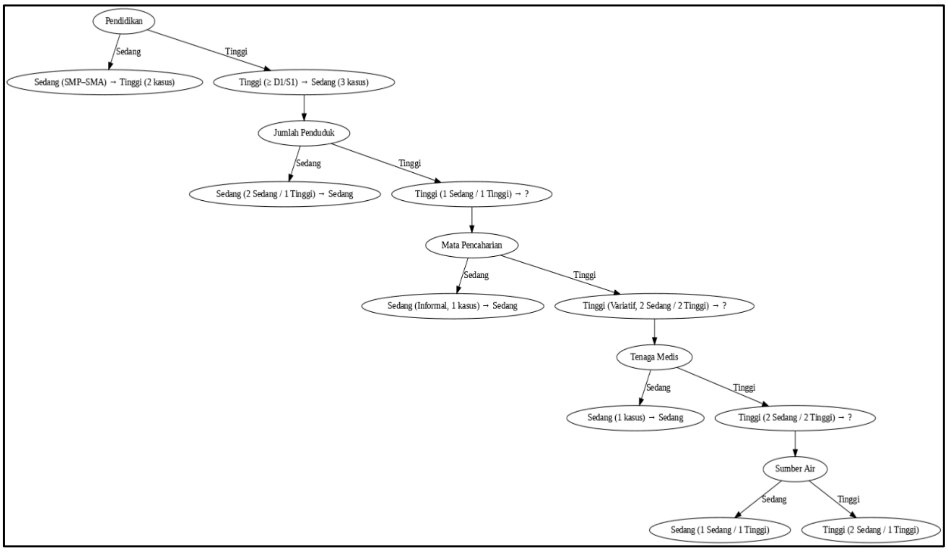

Figure 3. Decision Tree Sosial

The infrastructure dataset comprised energy sources, school facilities, health facilities, transportation, and water infrastructure. The overall welfare classification based on these indicators is displayed in Figure 4.

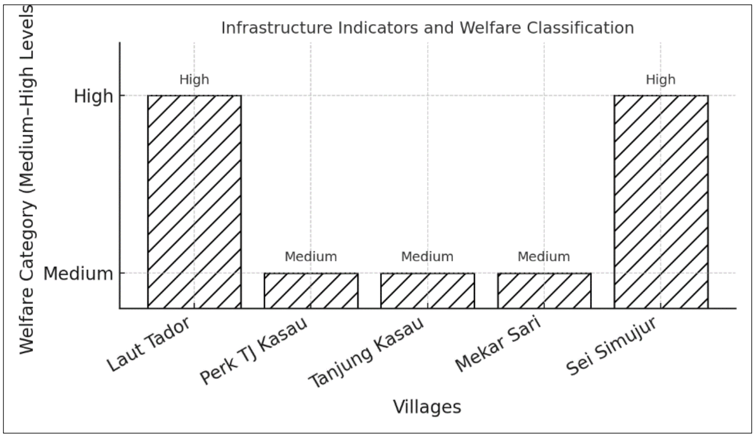

Figure 4. Distribution of Infrastructure Indicators

The Decision Tree results show that energy sources are a dominant factor in determining welfare levels among social variables. Villages with higher levels of education generally achieve better welfare classifications, supported by supporting attributes such as health facilities, infrastructure conditions, school facilities, and clean water sources. The resulting model is shown in Table 2.

Table 2. Attribute Importance of Infrastructure Indicators (C4.5)

Atribut	Criteria	Total (S)	Medium	High	Entropy	Gain	Split Info	Gain Ratio
Total	—	5	3	2	0.97095059			

Health Facilities	Medium	3	2	1	0.91829583	0.01997309	0.970950 59	0.02057066
	High	2	1	1	1			
Energy Sources	Medium	3	3	0	0	0.57095059	0.970950 59	0.58803259
	High	2	0	2	0			
Infrastructure Conditions	Medium	1	0	1	0	0.3219281	0.7219281	0.445928
	High	4	3	1	0.81127812			
Water Facilities	Medium	3	3	1	0.52832083	0.019973	0.970950 59	0.020571
	High	2	0	1	0			
School Facilities	Medium	2	2	0	0	0.419973	0.970950 59	0.43253797
	High	3	1	2	0.91829583			

A similar classification structure was produced for infrastructure indicators. The tree reveals how infrastructure-related attributes determine welfare levels across villages, with the root and branching nodes representing the most influential factors. The result is displayed in Figure 5.

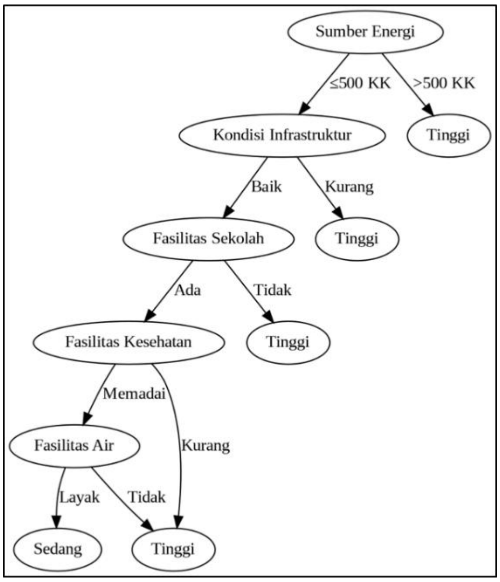

Figure 5. Decision Tree Infrastruktur

The model's reliability was tested using the 10-fold cross-validation technique. Table 5 summarizes the evaluation metrics for both datasets.

Table 3. Model Validation and Performance

Metric	Social Indicators	Infrastructure Indicators
Accuracy	100%	100%
Precision	1.00	1.00
Recall	1.00	1.00
F1-score	1.00	1.00

The model's performance was then evaluated to ensure the reliability of the classification results. Accuracy testing demonstrated that the Decision Tree achieved a consistent and acceptable level of performance across both datasets, confirming its suitability for analyzing village welfare. The evaluation metrics are summarized in the following Table 4.

Table 4. Confusion matrix indicator social and infrastruktur

Aktual	Medium	High
Medium	3 (True Positive)	0 (False Positive)
High	0 (False Negative)	2 (True Negative)

The performance metrics in Table 4 indicate that the C4.5 Decision Tree achieved reliable accuracy in classifying village welfare levels. To complement these numerical results, a confusion matrix was generated from the Python implementation. This visualization provides a clearer picture of the model's classification outcomes by showing the distribution of correctly and incorrectly classified cases. The confusion matrix is presented in Figure 6.

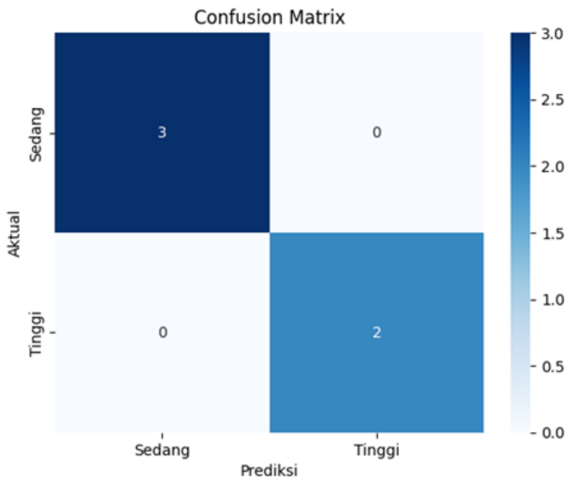

Figure 6. Confusion Matrix dari Colab

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Akurasi Total = 100.00%
Akurasi per label:
              precision    recall  f1-score   support

      Sedang       1.00      1.00      1.00         3
      Tinggi       1.00      1.00      1.00         2

    accuracy                           1.00         5
   macro avg       1.00      1.00      1.00         5
weighted avg       1.00      1.00      1.00         5
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Figure 7. Classification Report

DISCUSSION

The primary objective of this study was to identify the dominant factors influencing village welfare in Laut Tador Sub-district using social and infrastructure indicators. By implementing the C4.5 Decision Tree algorithm, this research contributes to the growing application of data mining techniques in social and rural development studies, an area that has been relatively underexplored.

The results reaffirm the importance of education and energy as key determinants of welfare status. Education was identified as the most influential social indicator, while energy availability emerged as the dominant infrastructure factor. These findings highlight the critical role of human capital and basic infrastructure in shaping welfare outcomes across villages. In this regard, the study aligns with the Capability Approach, which emphasizes education as an enabler of individual and collective well-being, and with the Infrastructure-led Development Theory, which underscores access to energy as a driver of rural progress.

Compared to previous studies, this study provides computational evidence that reinforces previous descriptive findings. For example, to emphasize the role of local participation in improving welfare (Nurhidayati, 2023), While another finding confirms the importance of infrastructure utilization (Atifah et al., 2023), However, both studies remain descriptive in nature. By applying the C4.5 algorithm, this study offers a systematic and quantitative approach to identifying the most decisive factors. Similarly, the results of this study complement the work of (Jannah et al., 2023) and (Yemi et al., 2024). Who applied decision trees in other community contexts, showing that this method can also be effectively applied in rural welfare analysis.

Beyond theoretical alignment, the findings carry several practical implications for local policy. Policymakers and village administrations should prioritize investments in education and energy provision, as these two factors demonstrate the highest impact on welfare outcomes. Strengthening the quality and accessibility of educational facilities, training local teachers, and ensuring reliable energy access across all households could significantly improve living standards. Moreover, developing integrated rural programs that combine educational empowerment with infrastructure improvement would create synergistic effects on welfare. The results can serve as an evidence-based reference for allocating village budgets more efficiently, ensuring that limited resources target sectors with the greatest welfare impact.

Nevertheless, the results should be interpreted with caution due to certain limitations. The study was conducted using data from a relatively small number of villages, which may limit the generalizability of the findings to broader rural contexts. Additionally, the dataset relied solely on indicators available from the Prodeskel Kemendagri database, which may not capture other relevant dimensions such as income distribution, environmental quality, or social capital. These limitations indicate that the model's predictive power may not fully represent the complexity of welfare dynamics in diverse village settings.

For future research, expanding the dataset to include more villages and incorporating additional indicators such as economic productivity, environmental sustainability, and community participation would enhance the comprehensiveness and external validity of the findings. Furthermore, comparing the C4.5 algorithm with other machine learning techniques such as Random Forest or Support Vector Machines could provide deeper insights into the most suitable computational methods for welfare classification in rural development contexts.

CONCLUSION

This study advances the understanding of village welfare determinants by applying the C4.5 Decision Tree algorithm to integrate social and infrastructure indicators within a data-driven analytical framework. The research contributes methodologically by demonstrating how computational models can identify dominant welfare factors with high accuracy and interpretability, bridging the gap between traditional descriptive studies and quantitative evidence-based policymaking. Substantively, it highlights education and energy availability as pivotal levers for improving rural welfare, emphasizing the joint significance of human capital and basic infrastructure in sustainable village development.

While the model showed robust classification performance, its scope remains limited to a small dataset from Laut Tador Sub-district and indicators sourced solely from Prodeskel Kemendagri. Future studies should extend this framework by incorporating economic, environmental, and social participation variables across multiple regions. Moreover, comparative analyses using alternative algorithms such as Random Forest, Gradient Boosting, or Support Vector Machinesbcould provide deeper methodological insights and enhance predictive generalization.

From a policy standpoint, the findings encourage local governments to leverage data mining tools for welfare mapping and prioritization. Tailoring educational initiatives and expanding equitable energy access can serve as actionable strategies to strengthen village resilience and promote inclusive rural development.

LIMITATION

This study has several limitations that need to be acknowledged. First, the analysis was based on data from only five villages in Laut Tador Sub-district. The relatively small scope may restrict the generalizability of the results to broader rural contexts. Second, the indicators used in this research were limited to those available in the Prodeskel Kemendagri database, which did not cover other important dimensions of welfare such as income distribution, environmental conditions, or community participation. These omissions may have influenced the comprehensiveness of the welfare classification.

Furthermore, the study relied exclusively on the C4.5 Decision Tree algorithm. While the method demonstrated reliable accuracy, alternative machine learning techniques could potentially reveal different dominant factors or improve model performance. These limitations indicate that the findings should be interpreted with caution and primarily within the specific research context.

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