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Data-Driven Insights Into Underdeveloped Regencies: SHAP-Based Explainable Artificial Intelligence Approach

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ABSTRACT

Classification analysis in high-dimensional data presents significant challenges, particularly due to the presence of complex non-linear patterns that traditional methods, such as logistic regression, fail to capture effectively. This limitation is often reflected in relatively low model accuracy. One approach to addressing this issue is through machine learning-based classification methods, such as Random Forest and Support Vector Machine (SVM). While these models generally achieve higher accuracy than logistic regression, their black-box nature limits interpretability, making it difficult to explain their classification decisions. As machine learning models continue to advance, interpretability has become a crucial concern, especially in data-driven decision-making. Post-hoc explainable artificial intelligence (XAI) techniques offer a viable solution to enhance model transparency. This study applies SHAP to machine learning models to gain insights into the underdevelopment status of regencies in Indonesia. The results indicate that SVM outperforms both logistic regression and Random Forest. SHAP values estimated from SVM, using various permuted variable subsets, exhibit stability. Clustering analysis identifies five optimal clusters of underdeveloped regencies. Based on average SHAP values, underdevelopment alleviation strategies should focus on social factors (Cluster 1), infrastructure (Cluster 2), accessibility (Cluster 3), and a combination of infrastructure, accessibility, education, and healthcare (Cluster 4), while Cluster 5 requires improvements in accessibility and economic conditions.

1. Introduction

High-dimensional data analysis poses inherent challenges in statistical modeling due to the complexity of inter-variable relationships and the heightened risk of overfitting, particularly in classification models. In classification analysis, logistic regression is one of the most commonly employed statistical methods, as it offers high interpretability and facilitates the assessment of each predictor variable's influence on the response variable [1]. Nevertheless, logistic regression has inherent limitations in capturing non-linear patterns and complex inter-variable interactions. Additionally, issues such as multicollinearity and data imbalance can adversely impact model performance, particularly in terms of accuracy [2, 3]. Compared to logistic regression, machine learning models such as Random Forest and Support Vector Machine (SVM) are better equipped to capture complex data patterns and enhance predictive accuracy [4, 5]. Despite their ability to achieve high predictive accuracy, machine learning models do not provide insights into their decision-making process, classifying them as black-box models [6].

Complex predictive models can generate highly accurate predictions; however, they often remain difficult for policymakers to interpret. As machine learning models continue to evolve, the challenge of interpretability has become an increasingly critical concern, particularly in data-driven decision-making. Model interpretability is essential to ensure that decisions derived from these models are reliable and grounded in a solid foundation. Therefore, there is a growing need for approaches that not only deliver high accuracy but also provide clear justifications for each prediction. Consequently, the demand for Explainable Artificial Intelligence (XAI) has emerged as a means to enhance trust in machine learning models. Ali, et al. [7] explained the types of explainability in XAI, namely: (i) data explainability, (ii) model explainability, (iii) post-hoc explainability, and (iv) assessment of explanations. Data explainability focuses on the transparency of data sources, data quality, and how data is processed before being used in a model. This ensures that the data utilized is representative of the problem being addressed. Model explainability involves understanding the model’s structure, parameters, and decision-making processes. Post-hoc explainability emphasizes explanations provided after the model generates predictions or decisions, whereas assessment of explanations highlights the role of expert knowledge in evaluating explanations to ensure their accuracy and practical utility.

The post-hoc explainability approach plays a crucial role in enhancing the understanding and trustworthiness of AI models, particularly in the context of complex and inherently opaque machine learning models. Post-hoc methods are often model-agnostic, meaning they can be applied to various machine learning models, ranging from simple to highly complex, without requiring modifications to the original model structure. This enables users to obtain explanations for existing models in a more accessible manner without the need to reconstruct them. Shapley Additive Explanations (SHAP) is a model-agnostic post-hoc explainability method based on game theory. It quantifies the contribution of each predictor to the model’s predictions at both global and local levels, providing a comprehensive understanding of feature importance in machine learning models [8]. In local interpretation, SHAP assigns values to each observation, enabling users to understand the rationale behind a prediction by quantifying the contribution of each predictor [9]. In global interpretation, the aggregation of SHAP values reveals the extent to which each predictor contributes to the response variable, either positively or negatively. This approach is similar to a variable importance plot but provides additional insights by indicating whether each predictor has a positive or negative relationship with the response variable. [7].

This technique serves as an essential tool in machine learning analysis, particularly in interpreting the impact of predictor variables on classification probabilities in high-dimensional data. By providing clearer interpretations, analytical results become more easily communicable to stakeholders and can be leveraged for more targeted policy decision-making. As an application of this approach, this study employs SHAP to analyze the variables contributing to regency underdevelopment in Indonesia. Addressing underdeveloped regions is a critical issue in national development planning, and data-driven analysis can offer deeper insights for policymakers. The dataset used in this study is highly multidimensional, consisting of 22 predictor variables and 415 observations. Logistic regression is employed as the baseline model for binary classification due to its simplicity and interpretability. To capture the non-linear relationships between predictor variables and the response variable, this study incorporates machine learning models, specifically Random Forest and Support Vector Machine (SVM), to enhance predictive accuracy.

By leveraging SHAP, this study not only emphasizes model accuracy but also ensures that the results are interpretable and practically applicable in decision-making processes. Furthermore, the determinants of regency underdevelopment may vary across regions depending on their specific conditions. Research related to underdeveloped regencies in Indonesia has been conducted by Oktora [10], which examined the determinants of regency underdevelopment status through a non-parametric approach, specifically Multivariate Adaptive Regression Splines (MARS). Purwandari and Hidayat [11] employed discriminant analysis as a parametric approach to identify the determinants of underdeveloped regencies. Otok, et al. [12] applied machine learning techniques, particularly the decision tree algorithm, to classify underdeveloped regions. Maulidina and Oktora [13] investigated the variables influencing underdeveloped regencies, with a specific focus on Eastern Indonesia, using a spatial approach. Lewenussa and Rawi [14] conducted a classification of underdeveloped regions, concentrating exclusively on one province, West Papua Province. Suyanto [15] constructed clusters of underdeveloped regions in general based on regional characteristics. While these studies have identified variables influencing underdevelopment in regencies broadly (applicable to all regencies), they have not specifically pinpointed the key determinants of underdevelopment at the instance level (for each regency). Such identification is critical for formulating policies that can be directly targeted to each underdeveloped regency. The local interpretations generated by SHAP—highlighting the most influential predictor variables for each regency's underdevelopment status—are highly valuable for policy formulation, allowing targeted interventions at the regency level. To enhance interpretability, the SHAP values will be analyzed through cluster analysis to categorize underdeveloped regencies into distinct groups. This approach provides a clearer understanding of the key variables that should be prioritized in designing programs aimed at alleviating underdevelopment in each regency. Based on this background, this study aims to:

1. Provide a comprehensive overview of regency underdevelopment in Indonesia and its influencing variables during the National Medium-Term Development Plan (RPJMN) period of 2000–2024;
2. Develop a predictive model for regency underdevelopment in Indonesia using Logistic Regression, Random Forest, and Support Vector Machine (SVM);
3. Identify the key variables influencing regency underdevelopment status in Indonesia using the model-agnostic SHAP approach;
4. Conduct cluster analysis based on the SHAP values.

2. Method

2.1. Research Coverage

The unit of analysis in this study comprises all regencies in Indonesia classified as underdeveloped based on Presidential Regulation (Perpres) No. 63 of 2020. The study covers a total of 415 regencies, of which 62 are classified as underdeveloped, while the remaining 353 are non-underdeveloped regencies. The Thousand Islands Regency is excluded from the analysis, as it is an administrative regency under the jurisdiction of the DKI Jakarta provincial government and possesses distinct characteristics compared to other regencies. The following is a list of underdeveloped regencies as defined by Perpres No. 63 of 2020.

Table 1. Underdeveloped Regencies During the RPJMN 2020–2024 Period

No	Province	Regency	No	Province	Regency
1	North Sumatera	Nias	32	North Mauku	Taliabu Islands
2	North Sumatera	South Nias	33	West Papua	Wondama Bay
3	North Sumatera	North Nias	34	West Papua	Bintuni Bay
4	North Sumatera	West Nias	35	West Papua	South Sorong
5	West Sumatera	Mentawai Islands	36	West Papua	Sorong
6	South Sumatera	North Musi Rawas	37	West Papua	Tambrauw
7	Lampung	West Coast	38	West Papua	Maybrat
8	West Nusa Tenggara	North Lombok	39	West Papua	South Manokwari
9	East Nusa Tenggara	West Sumba	40	West Papua	Arfak Mountains
10	East Nusa Tenggara	East Sumba	41	Papua	Jayawijaya
11	East Nusa Tenggara	Kupang	42	Papua	Nabire
12	East Nusa Tenggara	South Central Timor	43	Papua	Paniai
13	East Nusa Tenggara	Belu	44	Papua	Puncak Jaya
14	East Nusa Tenggara	Alor	45	Papua	Boven Digoel
15	East Nusa Tenggara	Lembata	46	Papua	Mappi
16	East Nusa Tenggara	Rore Ndao	47	Papua	Asmat
17	East Nusa Tenggara	Central Sumba	48	Papua	Yahukimo
18	East Nusa Tenggara	Southwest Sumba	49	Papua	Bintang Mountains
19	East Nusa Tenggara	East Manggarai	50	Papua	Tolikara
20	East Nusa Tenggara	Sabu Raijua	51	Papua	Keerom
21	East Nusa Tenggara	Malaka	52	Papua	Waropen
22	Central Sulawesi	Donggala	53	Papua	Supiori
23	Central Sulawesi	Tojo Una-una	54	Papua	Greater Mamberamo

24	Central Sulawesi	Sigi	55	Papua	Nduga
25	Maluku	West Southeast Maluku	56	Papua	Lanny jaya
26	Maluku	Aru Islands	57	Papua	Central Mamberamo
27	Maluku	West Seram	58	Papua	Yalimo
28	Maluku	East Seram	59	Papua	Puncak
29	Maluku	Southwest Maluku	60	Papua	Dogiyai
30	Maluku	South Buru	61	Papua	Intan Jaya
31	North Maluku	Sula Islands	62	Papua	Deiyai

The variables used in this study consist of a response variable, namely the underdevelopment status (1 = Underdeveloped Regency, 0 = Non-Underdeveloped Regency), and 22 predictor variables. All variables are based on 2021 data obtained from Statistics Indonesia (BPS) and the Ministry of Finance. Some of the data used in this study were obtained from BPS (Statistics Indonesia), specifically from the Village Potential Statistics of Indonesia (PODES) and the National Socio-Economic Survey (SUSENAS). PODES is a census-based data collection effort that covers all administrative regions, including regencies/municipalities, districts, and the lowest-level government administrative units equivalent to villages. In contrast, SUSENAS is a regular household-based survey conducted by BPS, providing essential socio-economic development data. SUSENAS is carried out in March and September each year. This study utilizes data from the March round of SUSENAS, which includes a sample of approximately 345,000 households and allows for statistical reporting at the national, provincial, and regency/municipality levels. All data used in this study are from the year 2021, aligned with the classification of underdeveloped regencies outlined in the 2020–2024 National Medium-Term Development Plan (RPJMN).

Table 2. Predictor Variables and Data Sources

Variable	Description	Data Source
X1	Percentage of villages with retail stores	PODES, BPS
X2	Percentage of villages with healthcare facilities	PODES, BPS
X3	Percentage of villages with doctors	PODES, BPS
X4	Percentage of villages with primary schools	PODES, BPS
X5	Percentage of villages with junior high schools	PODES, BPS
X6	Percentage of households with electricity access	SUSENAS, BPS
X7	Percentage of households with telephone/mobile phone access	SUSENAS, BPS
X8	Percentage of population using the internet	SUSENAS, BPS
X9	Percentage of households with access to clean water	SUSENAS, BPS
X10	Percentage of villages where the main road surface is predominantly asphalt/concrete	PODES, BPS
X11	Percentage of villages with easy access to healthcare facilities	PODES, BPS
X12	Percentage of villages with easy access to junior high schools	PODES, BPS
X13	Percentage of villages not experiencing natural disasters	PODES, BPS
X14	Percentage of villages not experiencing social conflicts	PODES, BPS
X15	Gross Regional Domestic Product (GRDP) at constant prices per capita (million IDR)	BPS
X16	Percentage of household expenditure on non-food items	SUSENAS, BPS
X17	Percentage of employed individuals working in non-agricultural sectors	SUSENAS, BPS
X18	Percentage of women aged 15–49 who gave birth in the past two years assisted by medical professionals	SUSENAS, BPS
X19	Percentage of children under five receiving complete immunization	SUSENAS, BPS
X20	Junior high school enrollment rate	SUSENAS, BPS
X21	Senior high school enrollment rate	SUSENAS, BPS
X22	Locally-Generated Revenue (PAD) per capita (thousand IDR)	Ministry of Finance

Notes: BPS (Badan Pusat Statistik) = Statistics Indonesia
PODES = Potensi Desa = Village Potential Statistics of Indonesia
SUSENAS = Survei Sosial Ekonomi Nasional = National Socio-Economic Survey

2.2. Analysis Method

The analysis methods used in this research include descriptive and predictive analyses. The descriptive analysis employs a thematic map to provide an overview of the distribution of underdeveloped regencies and a boxplot to illustrate the data distribution of the predictor variables involved. Additionally, SHAP and cluster analysis are utilized to assess the contribution of the variables determining these underdeveloped regions. Predictive analysis is conducted using logistic regression, Random Forest, and SVM. Logistic regression serves as a representation of a traditional statistical classification model, while Random Forest and SVM represent black-box models expected to deliver higher accuracy compared to the logistic regression model. The stages undertaken in this research are as follows:

1. Conduct descriptive analysis using thematic maps and boxplots
2. Separate the data into training and testing sets with an 80:20 ratio
3. Modeling with logistic regression
   - Perform logistic regression modeling with training data. The logistic regression estimation equation is as follows:
   $$logit\ [\hat{\pi}(x)] = \ln\frac{\hat{\pi}(x)}{1-\hat{\pi}(x)} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \beta_{22} x_{22}$$
   - Predicting underdeveliped regencies from the logistic regression estimation equation formed using the testing data.
4. Modeling with Random Forest
   - Random Forest modeling using training data with parameter cp: 0,01; minsplit: 20, maxdepth: 30, dan xval: 10
   - Predicting underdeveloped regencies from the Random Forest model formed using testing data
5. Modeling with SVM
   - SVM modeling using training data with parameters Kernel = "radial", cost = 100, gamma = 0.1
   - Predicting underdeveloped regencies from the SVM model formed using testing data
6. Constructing a classification table to summarize the results of logistic regression, Random Forest, and SVM models. The classification table, as shown in Table 3, consists of four cells containing the values for true positive (TP), which represents the success category correctly predicted as success; false negative (FN), where the success category is incorrectly predicted as failure; true negative (TN), where the failure category is correctly predicted as failure; and false positive (FP), where the failure category is incorrectly predicted as success. In this context, the success category refers to underdeveloped regencies, while the failure category refers to non-underdeveloped regencies.

   Table 3. Classification Table

		Predicted	
		Success	**Failure**
Observed	**Success**	TP	FN
	Failure	FP	TN

   Based on the classification table, the following performance metrics can be derived: Sensitivity (True Positive Rate): The probability that the success category is correctly predicted. Specificity (True Negative Rate): The probability that the failure category is correctly predicted. Accuracy: The ratio of correct predictions (both success and failure) to the total number of predictions
   $$Sensitivity = \frac{TP}{TP+FN}$$
   $$Specificity = \frac{TN}{TN+FP}$$
   $$Accuracy = \frac{TP+TN}{TP+FN+TN+FP}$$
7. Selecting the best model based on the highest accuracy, followed by a post-hoc XAI analysis using SHAP
8. Using the SHAP method to compute the Shapley values for each observation through the following steps [8, 16]:
   - Selecting 100 random samples from the set of permuted subsets of 22 variables using the Monte Carlo sampling approach. The utilization of samples in SHAP value

computation is necessitated by the large number of variables involved, which renders the use of all possible subset permutations inefficient.
- Estimating the Shapley value for variable i (ϕ_i) for each sample using the following formulation:

$$\phi_i = \sum_{S \subseteq F\{i\}} \frac{|S|!\,(|F| - |S| - 1)!}{|F|!} \left[f_{S\cup\{i\}}\left(x_{S\cup\{i\}}\right) - f_S(x_s)\right]$$

wehre F represents the set of sampled variables, x_S represents the value of the input variables in the set S
- Calculating the average SHAP value from the 100 sampled observations

9. Repeating Step 8 for 10 randomly selected iterations for underdeveloped regencies. This process will be demonstrated for one underdeveloped regency, namely Southwest Maluku. The ten SHAP values for each variable will be presented in a boxplot to assess the stability of the estimated SHAP values for each variable.
10. Displaying the SHAP value plots, demonstrated for two regencies: Southwest Maluku and Mentawai Islands.
11. Performing cluster analysis using hierarchical clustering, a method used to construct a hierarchy of clusters. Hierarchical clustering has an advantage over partition-based clustering methods, as it does not require specifying the number of clusters in advance [17, 18]. SHAP value cluster analysis is conducted through the following steps:
- Summing the SHAP values for each underdeveloped regency into six variable groups: economy, health, education, accessibility, social, and infrastructure.
- Selecting the best linkage method based on the Agglomerative Coefficient (AC), calculated using the following formula [19] :

$$AC = \frac{1}{n}\sum_{i=1}^{n} l(i)$$

where

$$l(i) = \frac{h(i) - \min(h)}{\max(h) - \min(h)}$$

$h(i)$: linkage height when the object i joins the hierarchical clustering
$\min(h)$: minimum value of linkage height in the dendrogram
$\max(h)$: maximum value of linkage height in the dendrogram
The AC value ranges from 0 to 1, where the higher the AC value (closer to 1), the stronger the cluster structure formed.
- Selecting the optimal number of K by using Gap Statistics [20]
- Determine the average SHAP value of each group of variables for each cluster
- Evaluate the clusters formed by comparing the group means of variables between clusters through Multivariate Analysis of Variance (MANOVA). This method requires the fulfillment of assumptions such as multivariate normal and homogeneity of variance. If these assumptions are not met, an alternative that can be used is a non-parametric method based on permutation tests, namely Permutational Multivariate Analysis of Variance (PERMANOVA) [21].
- Interpreting the results of cluster

3. Results and Discussion

3.1. Overview of Underdeveloped Regencies in Indonesia

Development disparities in Indonesia have led to certain regencies being less developed compared to others. In 2020, the government designated 62 regencies as underdeveloped, distributed across the country. As illustrated in Fig. 1, the majority of these underdeveloped regencies are concentrated in Eastern Indonesia, particularly in the Maluku Islands (8 regencies) and Papua Island (30 regencies). In Central Indonesia, underdeveloped areas are found in Sulawesi Island (3 regencies) and the Nusa Tenggara Islands (14 regencies). Meanwhile, in Western Indonesia, there are 7 underdeveloped regencies, all of which are located on Sumatra Island.

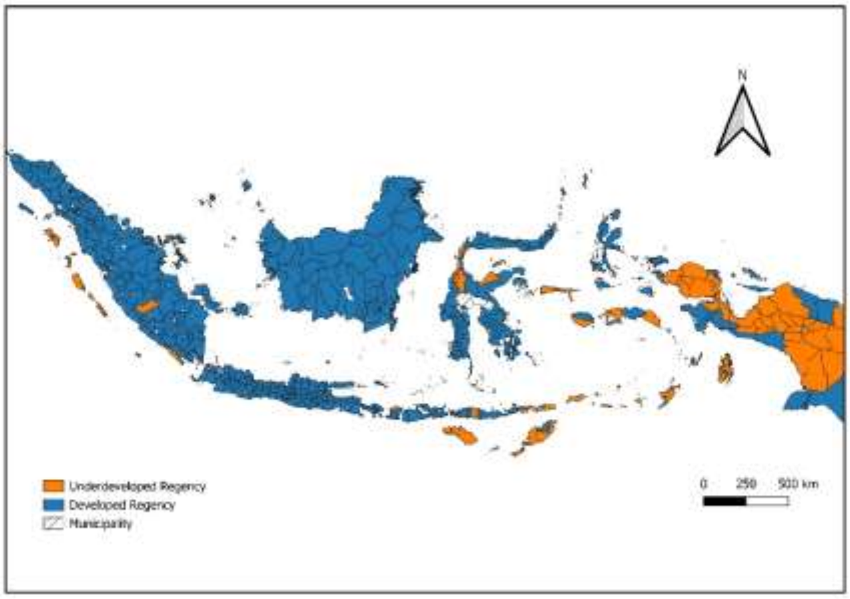

Fig. 1. Map of the Distribution of Underdeveloped Regencies

Based on Fig. 2, variables exhibiting significant variation among underdeveloped regencies include the percentage of villages with elementary schools (X4), the percentage of villages that did not experience natural disasters (X13), and the percentage of villages with the widest main road surface made of asphalt/concrete (X10). The median values of predictor variables for underdeveloped regencies are lower than those for developed regencies, except for the percentage of villages that did not experience natural disasters (X13). The variable with the highest median in underdeveloped regencies is the percentage of villages that did not experience social conflicts (X14).

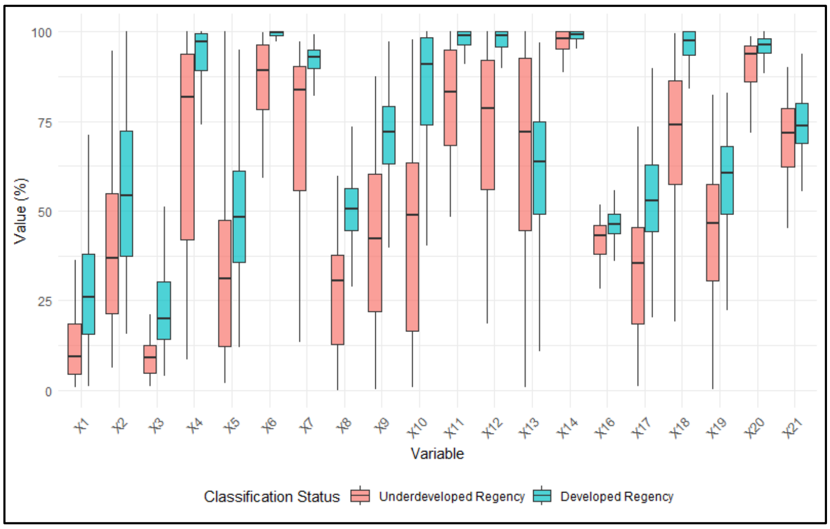

Fig. 2. Boxplot of Predictor Variables by Classification Status

A stark contrast between underdeveloped and developed regencies is evident in the percentage of households with electricity access (X6), where nearly all developed regencies have reached 100 percent, whereas some underdeveloped regencies still have percentages below 75 percent. Disparities are also observed in the percentage of villages with the widest main road surface made of asphalt/concrete (X10), as many underdeveloped regencies still have poor road access. The lowest median values are found in the percentage of villages with retail stores (X1) and the percentage of villages with doctors (X3).

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3.2. Model Performance Comparison: Logistic Regression, Random Forest, and Support Vector Machine

Based on Table 4, the evaluation of the three models using testing data indicates that the Support Vector Machine (SVM) exhibits the highest sensitivity, achieving a value of 0.8333. This implies that 83.33% of regencies classified as underdeveloped are correctly identified by the model. Meanwhile, the highest specificity is attained by both the Random Forest and SVM models, with an identical value of 0.9714, signifying that 97.14% of regencies classified as developed are accurately predicted. In terms of overall classification performance, SVM demonstrates the highest accuracy. The superior predictive capability of SVM over Random Forest is consistent with findings from prior studies that have compared the efficacy of these machine learning models in similar classification tasks [22-24]. Based on these results, the subsequent post-hoc analysis using SHAP will be conducted with reference to the SVM model.

Table 4. Comparison of Model Performance Using Testing Data

Method	Sensitivity	Specificity	Accuracy
Logistic Regression	0.7500	0.9571	0.9268
Random Forest	0.6667	**0.9714**	0.9268
Support Vector Machine	**0.8333**	**0.9714**	**0.9512**

3.3. Shapley Additive Explanations (SHAP)

Before proceeding with the SHAP method further, it is essential to assess the stability of SHAP values. This stability is crucial for drawing more reliable conclusions regarding which variables significantly contribute to identifying the underdevelopment status of a regency. The stability assessment is conducted by computing SHAP values for each variable in specific underdeveloped regencies (in this case, exemplified by Southwest Maluku Regency and Mentawai Islands Regency) using 100 samples drawn from the total permutation set of 22 variables, repeated across 10 iterations. The decision to use a sufficiently large sample size is based on the previous study by Zhang, et al. [25] with the expectation of reducing the error ratio in determining the most influential variables, the SHAP values for 10 iterations are presented in Fig. 3. The estimated SHAP values for each variable in Southwest Maluku Regency over 10 iterations exhibit a high degree of homogeneity, as evidenced by the maximum standard deviation of SHAP values for each variable being 0.05, observed in variable X14. Meanwhile, in the Mentawai Islands Regency, the highest standard deviation is 0.06, found in variable X6. Despite having the largest standard deviation among all variables, X14 in Southwest Maluku Regency consistently emerges as the most influential variable across all iterations. Similarly, SHAP values for X6 in Mentawai Islands Regency follow the same pattern

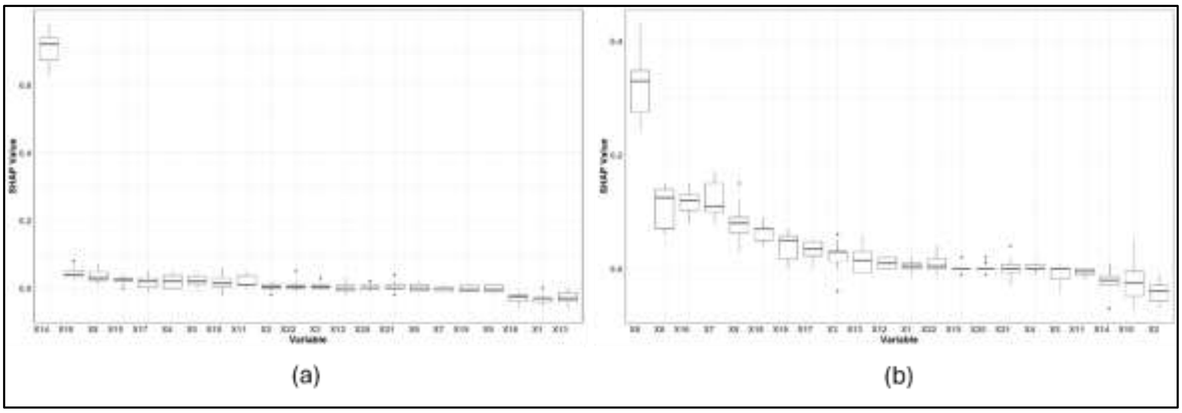
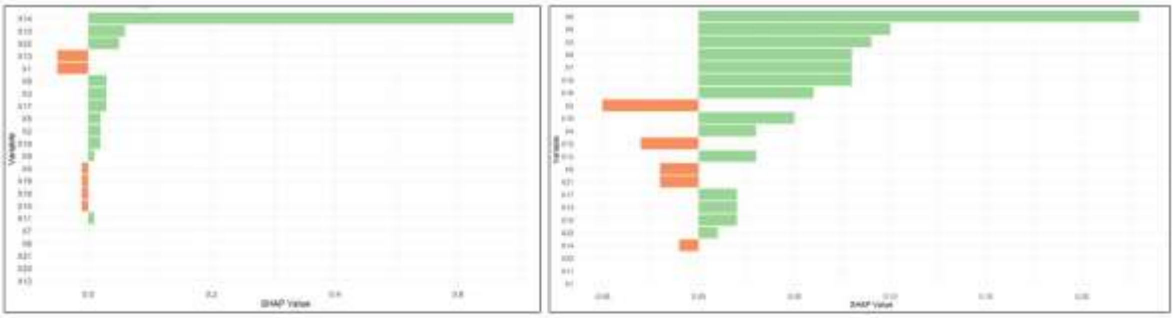


Fig. 3. Boxplot of Estimated SHAP Values for Each Predictor Variable Across 10 Iterations in (a) Southwest Maluku Regency and (b) Mentawai Islands Regency.

Since the variables with the highest contributions, as shown in Fig. 3, demonstrate sufficient stability, the SHAP method will be employed to explain the key contributing variables in each underdeveloped regency. Figure 4 presents an example of the SHAP value plots generated for (a) Southwest Maluku Regency and (b) Mentawai Islands Regency. The most influential variable in

Southwest Maluku Regency is the percentage of villages without social conflicts (X14), which falls under the social category. In contrast, in Mentawai Islands Regency, the key variable is the percentage of households using electricity (X6), which belongs to the infrastructure category



(a) (b)

Fig. 4. SHAP Values for (a) Southwest Maluku Regency, (b) Mentawai Islands Regency

3.4. Clustering of Regencies Based on SHAP Values

To facilitate the interpretation of SHAP values for the 62 underdeveloped regencies, clustering analysis was conducted using the Hierarchical Clustering method. Based on the Agglomerative Coefficient, the Ward method yielded the highest value (0.9321) compared to single linkage (0.5687), average linkage (0.8122), and complete linkage (0.8642). Therefore, the Ward method was selected as the optimal clustering approach. One of the advantages of the Ward method is its ability to minimize variance within clusters while simultaneously maximizing the distance between clusters [26]. To determine the optimal number of clusters, a simulation was conducted using randomly generated datasets of 500; 1,000; 5,000; and 10,000 samples. The optimal number of clusters was selected based on the highest gap statistic value observed before it subsequently declined. Based on the simulation results presented in Table 5, the optimal number of clusters was determined to be five.

Table 5. Simulation Results for Gap Statistics Calculation

K	B=500		B=1000		B=5000		B=10000	
	Gap	**SE**	**Gap**	**SE**	**Gap**	**SE**	**Gap**	**SE**
1	0.32675	0.02926	0.32424	0.02982	0.32641	0.02971	0.32601	0.02956
2	0.37102	0.03079	0.36962	0.03109	0.37176	0.03066	0.37114	0.03061
3	0.42822	0.03083	0.42606	0.02971	0.42846	0.02969	0.42791	0.02963
4	0.43770	0.03130	0.43732	0.02956	0.43873	0.02971	0.43810	0.02933
5	**0.45047**	**0.03018**	**0.45098**	**0.03002**	**0.45170**	**0.02953**	**0.45109**	**0.02895**
6	0.44581	0.02985	0.44676	0.03045	0.44701	0.02948	0.44644	0.02903
7	0.45387	0.02975	0.45474	0.03081	0.45489	0.02970	0.45440	0.02925
8	0.46933	0.03000	0.47023	0.03129	0.47045	0.02998	0.47008	0.02952
9	0.49889	0.03048	0.49957	0.03176	0.49978	0.03043	0.49962	0.02988
10	0.50937	0.03102	0.51000	0.03206	0.51022	0.03095	0.51020	0.03027

SE: Standard Error

To evaluate the formed clusters, a mean difference test was conducted to ensure that the clusters are distinct and can subsequently be used to identify variable groups (categories) that should be prioritized in addressing regency underdevelopment. Based on the results of the multivariate normality test and homogeneity of variance test, a p-value of less than 0.05 was obtained. Consequently, it can be concluded that the assumptions of multivariate normality and homogeneity of variance were not met. Therefore, the PERMANOVA method was employed to perform the multivariate mean difference test. The test results yielded a pseudo-F value of 30.38 with a p-value of 0.001. These findings indicate that at least one pair of clusters is significantly different. Subsequently, a post-hoc test was conducted using pairwise PERMANOVA to identify which cluster pairs exhibited significant differences. The test results are presented in Fig. 5.

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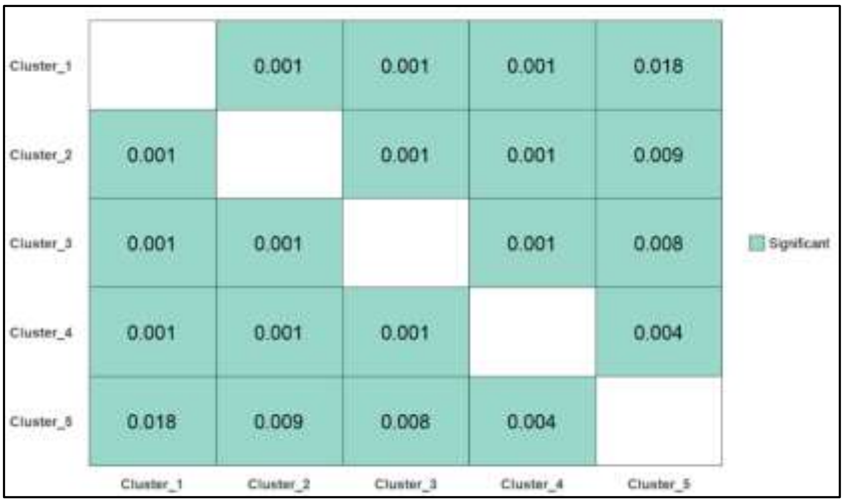

Fig. 5. P-Value Based on Pairwise PERMANOVA Test Results

Based on Fig. 5, it can be concluded that the average SHAP values for all cluster pairs differ at a significance level of 0.05. Thus, it can be concluded that each cluster is significantly different from the others. The clustering results obtained using the Hierarchical Clustering method with Ward's approach and five clusters are presented in Fig. 6.

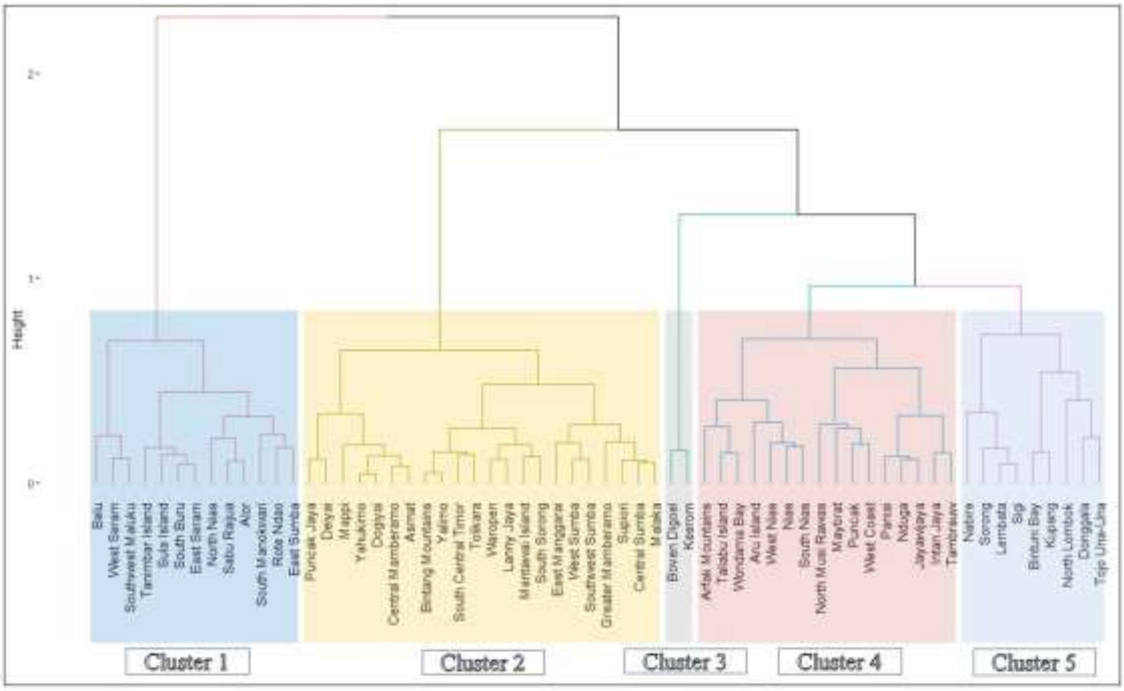

Fig. 6. Dendrogram of Underdeveloped Regencies with Five Clusters

The average SHAP values for each cluster are presented in Table 6. Based on these SHAP values, the key categories that the government should prioritize to alleviate underdevelopment in each cluster can be identified.

Table 6. Average SHAP Values by Cluster and Category

Cluster	Economy	Health	Education	Accesibility	Social	Infrastructure
1	0.0969	0.1346	0.0754	0.0915	**0.4492**	0.1062
2	0.1023	0.0955	0.0727	0.1227	0.0255	**0.5509**
3	0.0100	0.0350	0.0250	**0.8500**	0.0150	0.1900
4	0.0469	**0.2256**	**0.1281**	**0.1756**	0.0600	**0.3244**
5	**0.1744**	0.1378	0.0989	**0.2478**	0.0489	0.1011

Based on Fig. 6 and Table 6, the following explanations can be provided:

Cluster 1 consists of 13 regencies, predominantly from East Nusa Tenggara Province and Maluku Province. Additionally, there is one regency from North Sumatra Province, namely North Nias. In this cluster, the highest average SHAP value is observed in the social category, which dominates compared to other categories. The government should focus on variables related to social aspects, particularly addressing issues of social conflict within the community.

Cluster 2 is the largest cluster, comprising 22 regencies. This cluster is predominantly composed of regencies located in Eastern Indonesia, particularly in Papua Province. Additionally, there is one regency from Western Indonesia, namely Mentawai Islands Regency (West Sumatra Province). In this cluster, the highest average SHAP value is found in the infrastructure category. The government should prioritize addressing underdevelopment variables related to infrastructure, such as electricity supply, clean water access, and internet connectivity.

Cluster 3 consists of two regencies, both located in Papua Province (Boven Digoel and Keerom). In this cluster, the highest average SHAP value falls within the accessibility category. Efforts to alleviate underdevelopment in this cluster should focus on expanding asphalt/concrete road networks, as well as improving access to healthcare and educational facilities.

Cluster 4 comprises 16 regencies. A significant portion of the underdeveloped regencies in Western Indonesia fall into this cluster, including Nias, West Nias, South Nias, North Musi Rawas, and West Coast. Additionally, this cluster includes regencies from North Maluku Province (Taliabu Islands), Maluku Province (Aru Islands), and the remaining regencies from Papua and West Papua Provinces. In this cluster, relatively high average SHAP values are observed in the infrastructure, accessibility, education, and health categories.

Cluster 5 consists of nine regencies. This cluster includes three regencies located in Central Indonesia, specifically on Sulawesi Island (Donggala, Sigi, and Tojo Una-Una) and the Nusa Tenggara Islands (North Lombok, Kupang, and Lembata), as well as regencies in Eastern Indonesia (Sorong, Bintuni Bay, and Nabire). In this cluster, government efforts to address underdevelopment should focus not only on accessibility but also on economic development.

3.5. Discussion

The results of the analysis using the Random Forest algorithm, followed by interpretation through the SHAP method, indicate that the determinants of underdeveloped regencies vary significantly across regions in Indonesia. In western Indonesia, influential variables are predominantly related to infrastructure, and access to education and healthcare services. Conversely, in eastern Indonesia, basic infrastructure indicators such as access to electricity, clean water, and internet connectivity play a more prominent role. Furthermore, this study reveals that Maluku Province demonstrates a unique pattern, where social aspects—particularly those related to local social conflicts—emerge as critical determinants of underdevelopment, distinguishing it from other provinces in eastern Indonesia.

These findings are consistent with prior research, such as Deffinika, et al. [27], which emphasized the influence of geographical and spatial factors in shaping multidimensional poverty, thereby underlining the need for geographically targeted government interventions. Similarly, Shoesmith, et al. [28] highlighted the inefficacy of nationally implemented policies—such as Indonesia's radical decentralization program—when local conditions are not adequately considered, as exemplified in South Central Timor Regency, East Nusa Tenggara. The insights from this study can inform policymakers in designing more effective strategies for addressing regional underdevelopment and promoting equitable development across regions. A community-focused and context-sensitive approach is recommended, with programs tailored to the specific socio-economic characteristics of each province, island, or region.

Although the Random Forest method has been applied in previous studies for regional classification and spatial poverty analysis (e.g., Ramayanti, et al. [29]; Sukarna, et al. [30]; Ilma, et al. [31]), its integration with SHAP for interpreting the categorization of underdeveloped regencies in Indonesia remains relatively novel. This combined approach holds considerable potential, as it captures complex nonlinear relationships among variables and yields locally interpretable insights that can be directly linked to regional policy formulation.

4. Conclusion

The majority of underdeveloped regencies in Indonesia are located on Papua Island. The predictor variable with the highest median among underdeveloped regencies is the percentage of villages that have not experienced social conflict, while the variable with the lowest median is the percentage of villages with a doctor. Based on model performance, SVM outperforms logistic regression and Random Forest as the best model. The estimated SHAP values for each variable across 10 iterations exhibit homogeneity and sufficient stability. Therefore, the SHAP method can be reliably used to explain the key contributing variables in each underdeveloped regency. Cluster analysis results indicate that the optimal number of clusters for classifying underdeveloped regencies is five. Based on the average SHAP values obtained across all categories in each cluster, it can be concluded that underdevelopment alleviation efforts should prioritize the social category for Cluster 1, infrastructure for Cluster 2, accessibility for Cluster 3, infrastructure, accessibility, education, and health for Cluster 4, and both accessibility and economic development for Cluster 5. The study reveals that the determinants of underdeveloped regencies in Indonesia vary across regions, with infrastructure, education, and health access being more influential in the western part, while basic infrastructure such as electricity, clean water, and internet connectivity dominate in the eastern regions. Notably, Maluku Province exhibits a distinct pattern, where social conflict emerges as a key factor, highlighting the importance of geographically tailored interventions. These findings underscore the value of combining Random Forest with SHAP to capture regional complexities and support more targeted and effective development policies.

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Conflict of interest

The authors declare no conflict of interest.

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