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ORIGINAL

Machine Learning-based Classification of Developing Countries and Exploration of Country-Specific ODA Strategies

Clasificación de países en desarrollo basada en aprendizaje automático y exploración de estrategias de AOD específicas para cada país

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ABSTRACT

Introduction: this study aimed to develop a systematic methodology for classifying recipient countries using machine learning, with the premise that tailoring mid- to long-term ODA strategies to country characteristics is essential. Additionally, it sought to propose ODA policy directions considering the unique attributes of classified developing countries.
Methods: the research analyzed 166 countries, including both developed and developing nations, using SDG scores and GDP per capita as key indicators. Machine learning techniques, specifically neural network analysis and decision tree analysis, were employed for classification.
Results: the analysis resulted in the classification of the 166 countries into 12 distinct groups, with seven nodes representing developing countries. Each group exhibited unique characteristics that informed the development of country-specific ODA strategies
Conclusions: this study successfully developed a systematic classification methodology for recipient countries using machine learning. The resulting classification and proposed ODA strategies for each group provide a foundation for more targeted and effective ODA policies. This approach enables policymakers to tailor their strategies to the specific needs and characteristics of different developing country groups, potentially improving the impact and efficiency of ODA efforts.

Keywords: Country Classification Methodology; Machine Learning; Neural Network Analysis; Decision Tree Analysis.

RESUMEN

Introducción: este estudio pretendía desarrollar una metodología sistemática para clasificar a los países receptores utilizando el aprendizaje automático, con la premisa de que es esencial adaptar las estrategias de AOD a medio y largo plazo a las características de cada país. Además, pretendía proponer orientaciones políticas para la AOD teniendo en cuenta los atributos únicos de los países en desarrollo clasificados.
Métodos: la investigación analizó 166 países, tanto desarrollados como en desarrollo, utilizando como indicadores clave las puntuaciones de los ODS y el PIB per cápita. Para la clasificación se emplearon técnicas de aprendizaje automático, concretamente el análisis de redes neuronales y el análisis de árboles de decisión.
Resultados: el análisis dio como resultado la clasificación de los 166 países en 12 grupos distintos, con siete nodos que representaban a los países en desarrollo. Cada grupo presentaba características únicas que sirvieron de base para el desarrollo de estrategias de AOD específicas para cada país.
Conclusiones: este estudio ha desarrollado con éxito una metodología de clasificación sistemática de los países receptores mediante aprendizaje automático. La clasificación resultante y las estrategias de AOD propuestas para cada grupo sientan las bases de unas políticas de AOD más específicas y eficaces. Este enfoque permite a los responsables políticos adaptar sus estrategias a las necesidades y características

específicas de los distintos grupos de países en desarrollo, mejorando potencialmente el impacto y la eficacia de los esfuerzos de AOD.

Palabras clave: Metodología de Clasificación de Países; Aprendizaje Automático; Análisis de Redes Neuronales; Análisis de Árboles de Decisión.

INTRODUCTION

The importance of Official Development Assistance (ODA) to developing countries has been strongly emphasized in the international community from the perspective of sustainable development and poverty alleviation. The Sustainable Development Goals (SDGs), which aim to be achieved by 2030, underscore the necessity of international solidarity and cooperation, aiming for global coexistence and prosperity through mutual support among nations. However, as each developing country exhibits unique social, economic, and environmental characteristics, uniform ODA strategies are unlikely to yield significant results. Thus, tailored support strategies that align with the individual characteristics of each country are required, which necessitates effective methods for classifying countries.(1,2,3)

Systematically categorizing developing countries to establish ODA strategies suited to their unique traits can significantly contribute to the efficient allocation of ODA resources. Particularly, the SDGs encompass various social and economic challenges faced by individual nations, resulting in differing priorities across countries. In this context, SDG data serves as a crucial criterion for country classification and is essential for designing strategies aimed at sustainable development in developing countries.(4) Moreover, GDP, which reflects a country's economic and living standards, is a key dependent variable for assessing poverty reduction and economic growth—the ultimate goals of ODA. Combining SDG and GDP per capita data for analysis is thus valuable for systematically understanding the impact of ODA policies on the economic development of target countries.

This study aims to analyze countries, including both developing and developed nations, using SDG and GDP per capita data and propose ODA strategies tailored to the characteristics of each country group. To this end, machine learning techniques such as Neural Network Analysis and Decision Tree Analysis are employed to identify SDG factors influencing GDP and to explore the impact of their combinations on economic growth in detail. Ultimately, the study extracts developing countries separately to propose ODA strategy directions tailored to their characteristics, aiming to establish more effective and goal-oriented ODA strategies.

Previous studies have often analyzed ODA effectiveness using simple statistical methods such as regression analysis.(5,6) However, such approaches fail to adequately capture the complex interactions among independent variables and have limitations in multidimensional analysis. Therefore, this study employs machine learning techniques such as Neural Network Analysis and Decision Tree Analysis. Neural Network Analysis enables the identification of complex, nonlinear relationships and a deeper exploration of the interactions among various SDG factors affecting GDP. In addition, Decision Tree Analysis visually elucidates the conditions and patterns that determine the impact of each SDG factor on GDP, providing useful insights for country classification and strategy formulation.

Thus, this study seeks to deeply explore the relationship between SDGs and GDP through machine learning techniques, emphasizing the importance of country classification in setting ODA strategies for developing countries. Based on this, the study aims to propose strategic directions for ODA in developing countries, offering a foundation for more targeted and effective ODA policies in the future.

THEORETICAL DISCUSSION ON ODA STRATEGY FORMULATION BASED ON COUNTRY CLASSIFICATION AND FOREIGN CASE STUDIES

The Significance of ODA Strategy Formulation Based on Country Classification

Formulating ODA policies based on country classification holds significant value for the efficient and effective utilization of international aid resources. Developing countries exhibit diverse economic, social, and political environments,(7) and providing aid in a standardized manner without reflecting these differences can limit the effectiveness of assistance.(8) Therefore, strategic aid policies that incorporate the unique characteristics of recipient countries are essential. The significance and importance of ODA policy formulation based on country classification can be summarized as follows:

Efficient Resource Allocation

Optimization of Resources: By designing tailored aid policies based on country classification, it becomes possible to optimize limited ODA resources and focus them on areas where they are most needed.(7) For instance, distinct aid strategies are required for low-income countries suffering from severe poverty and for middle-income countries with a growing middle class. Such classification allows for setting goals aligned with each country's stage of development, thereby enhancing the efficiency of resource allocation.

Avoiding Duplication and Maximizing Impact: Country classification helps prevent overlapping aid efforts and enables concentrated investment in critical areas, thereby maximizing the effectiveness of assistance.[7]

Enhancing Effectiveness Through Tailored ODA Strategy Design

Tailored Strategies Based on Country Characteristics: Since each country has unique social and economic structures and developmental challenges, classification enables the formulation of aid strategies that align with the specific needs and circumstances of individual countries. For example, countries with weak healthcare systems may require enhanced support in health-related areas, while those with low agricultural productivity might benefit from aid focused on improving agricultural outputs.

Increased Aid Effectiveness: A tailored approach based on classification ensures that aid meets the actual needs of recipient countries, thereby increasing its effectiveness and significantly improving the likelihood of achieving its objectives. This approach also contributes to the achievement of the Sustainable Development Goals (SDGs), such as poverty alleviation, education, and health.

Improving Policy Consistency and Sustainability

Consistent ODA Strategies: Country classification supports maintaining policy consistency and generating sustainable outcomes. By providing ODA that considers each country's economic and political stability and institutional characteristics, it helps establish a foundation for long-term self-reliance.

Building Long-term Partnerships: Aid tailored through country classification contributes to creating a basis for self-reliance in recipient countries, enabling sustainable development even after the cessation of aid. This approach fosters long-term partnerships and strengthens the capacity of developing countries to sustain their own development.

Establishing a Performance Evaluation and Feedback System

Facilitating Performance Evaluation: Formulating ODA strategies based on country classification allows for more systematic performance evaluation of aid effectiveness. By setting goals and indicators tailored to the characteristics of each country, the outcomes of aid policies can be clearly assessed, and feedback can be used to refine and improve future policies.

Data-driven Decision-making: Country classification enables the analysis of each nation's developmental status based on data, facilitating the design of policies aligned with their specific needs. This data-driven approach enhances the precision of decision-making, increases the likelihood of successful aid, and serves as a valuable reference for future strategy development.

Strengthening International Responsibility and Contribution to Development Goals

Contributing to International Development Goals: Country classification facilitates more targeted contributions to achieving global Sustainable Development Goals (SDGs). By implementing ODA policies aligned with the specific objectives of each nation, it supports the efficient attainment of international goals such as poverty reduction, hunger eradication, and quality education.

Providing Responsible Aid: establishing policies through country classification underscores the donor country's responsibility to the international community while promoting the self-reliance and development of recipient countries. This approach lays the foundation for strengthening global solidarity and cooperation.

Thus, formulating ODA policies based on country classification plays a crucial role in maximizing resource allocation efficiency, supporting the self-reliance and development of recipient countries through tailored approaches, and enhancing the sustainability and international responsibility of aid.

Case Studies of Advanced Donor Countries

Advanced donor countries, such as Japan, Sweden, and Germany, provide efficient aid tailored to the characteristics of recipient countries through ODA strategies based on country classification. These nations contribute to achieving international development goals by formulating customized ODA strategies that consider the economic and social characteristics of recipient countries.

Japan

Japan adopts a strategic approach in its ODA policies by classifying recipient countries into middle-income and low-income categories based on their economic and social development levels.[9,10] This classification allows Japan to deliver differentiated aid, focusing particularly on infrastructure development and human resource development in Asia. Depending on the developmental level of the recipient country, Japan provides either financial assistance or technical support to meet specific needs.

From a strategic perspective, Japan supports middle-income countries by helping them establish self-reliance through technology transfer and economic cooperation, while prioritizing basic infrastructure and improved living standards in low-income countries by focusing on areas such as healthcare and education. Through these tailored support measures, Japan strengthens its economic and political partnerships, particularly within Asia, while aiming for the self-reliance of recipient countries.

Sweden

Sweden prioritizes its aid based on social values such as human rights, democracy, and gender equality, focusing on supporting environmental and social stability. Recipient countries are classified according to their levels of democracy and respect for human rights, enabling Sweden to provide ODA aimed at improving these social values in the respective countries.[11,12]

Sweden's key strategies include providing resources necessary for protecting human rights and establishing democratic institutions, particularly in low-income countries such as those in Africa. It also actively promotes programs for environmental sustainability. This approach reflects Sweden's commitment to human rights and environmental protection as core values, contributing to the long-term and sustainable development of recipient countries.

Germany

Germany classifies recipient countries based on their economic level, political stability, and social development status, providing multidimensional support tailored to these factors.[13,14] Germany primarily offers customized aid strategies in sectors such as healthcare, education, and the environment to developing and low-income countries in regions like Africa, the Middle East, and Asia.

Germany's key strategies focus on addressing global challenges such as resource sustainability, environmental protection, and climate change. By reflecting the economic levels and social needs of each country in its support, Germany maximizes the effectiveness of its aid. Additionally, Germany facilitates self-reliance in developing countries through initiatives like technology transfer and supports green energy transitions in the energy sector to achieve long-term development goals.

Review of Previous Studies

Major previous studies emphasizing the necessity of classifying developing countries and proposing differentiated ODA strategies tailored to each type can be categorized as follows:

Studies Focused on Economic Levels and Growth Potential

Burnside & Dollar[3]: this study argues that macroeconomic policies in developing countries significantly influence the effectiveness of ODA. It classifies recipient countries based on economic stability and growth potential, suggesting that concentrating ODA resources on countries with high growth potential can maximize aid effectiveness.

Clemens, Radelet & Bhavnani[5]: these researchers emphasize the need to differentiate between countries capable of achieving short-term economic growth and those aiming for long-term self-reliance. They conclude that focusing ODA resources on countries with promising short-term growth prospects is advantageous for improving aid performance.

Studies Focused on Social and Institutional Stability and Governance Levels

Collier & Dollar[6]: this study highlights the importance of classifying recipient countries based on governance and institutional stability to maximize the efficiency of ODA in reducing poverty. It argues that politically stable countries with low levels of corruption can utilize ODA resources more efficiently, yielding greater outcomes.

Hansen & Tarp[15]: this research claims that the performance of ODA is heavily influenced by the political environment and governance level of recipient countries. It emphasizes the necessity of distinguishing between countries with high social and institutional stability and those without, advocating for tailored support strategies for more stable nations.

Studies Focused on Poverty Levels and Humanitarian Needs

Sachs[16]: this study emphasizes the need for intensive aid to countries with high poverty rates or urgent humanitarian needs. Sachs argues that providing essential infrastructure and resources for basic living should be prioritized, particularly in regions like Africa, to break the cycle of poverty.

Alesina & Dollar[1]: these researchers highlight the importance of aligning ODA with the poverty levels of recipient countries. They stress that for countries with high poverty rates, aid should primarily focus on improving basic living conditions and supporting essential needs.

Studies Focused on Environmental Sustainability and Climate Change Adaptation

Bourguignon & Sundberg[2]: this study argues that environmental sustainability should be a critical criterion in ODA strategies. It advocates for identifying countries with high environmental vulnerability and providing tailored aid focused on environmental protection and climate change adaptation.

Easterly & Pfutze[17]: these researchers emphasize the necessity of long-term, sustainable ODA for countries vulnerable to climate change. They underscore the importance of customized aid for nations where environmental factors play a significant role in their development challenges.

Limitations of Previous Studies and Features of This Research

While previous studies have provided important indicators for formulating ODA policies, they also exhibit several limitations. This research addresses these shortcomings by employing machine learning techniques, offering more sophisticated and data-driven strategic insights.[18,19] The limitations of existing studies are outlined as follows:

First, a focus on analyzing the effects of individual variables. Previous studies often independently analyze the impact of a single SDG or isolated indicators on ODA outcomes, lacking consideration of the interactions between variables. For instance, economic growth, institutional stability, and environmental factors are frequently treated separately, limiting the comprehensive understanding of how SDGs collectively influence GDP. This fragmented approach fails to reflect the complex interconnections among SDGs in real-world scenarios.[20,21]

Second, reliance on standardized statistical methods. Many studies depend on traditional statistical techniques such as regression analysis, which struggle to detect nonlinear relationships or complex interactions. These methods are inadequate for capturing the interdependencies among various SDG indicators, thereby limiting their ability to reflect the multifaceted nature of development challenges.

Third, lack of data-driven approaches for differentiated strategies by country. Previous research often derives conclusions through case studies focused on specific regions or groups of countries, making generalization difficult and limiting the development of tailored strategies for individual countries.[7] To incorporate diverse indicators across nations and refine country-specific strategies, more advanced data analysis methods are needed, which traditional approaches fail to adequately provide.

Fourth, insufficient actionable insights for policy formulation.Previous studies frequently stop at simple correlation analyses, which are insufficient for generating concrete, practical insights necessary for policy development. They fail to identify complex SDG patterns or critical combinations of variables, resulting in limited applicability for setting detailed policy directions.

By addressing these limitations, this research employs advanced machine learning techniques to explore the intricate relationships among SDGs and their impact on GDP. This approach enables the generation of actionable insights and the development of tailored, data-driven ODA strategies for individual countries.

On the other hand, this research distinguishes itself from previous studies by offering the following advantages:

First, the ability to analyze nonlinear relationships and interactions among.[22,23] This study initially employs neural network analysis to investigate the complex nonlinear relationships between SDG indicators and GDP per capita. Neural network analysis is a model capable of reflecting the interactions among diverse independent variables, allowing it to detect nonlinear patterns in the relationship between SDGs and GDP. By complementing the limitations of traditional statistical methods, this approach enables a comprehensive analysis of the collective impact of SDG indicators on GDP.

Second, the extraction of key variables to enhance policy.[24,25] From the results of neural network analysis, the SDG indicators that have the most significant impact on GDP per capita are identified. Based on these findings, a secondary decision tree analysis is conducted to further elucidate specific patterns associated with key SDG indicators. This process visualizes the critical variables influencing GDP, presenting them in an accessible manner and providing clear indicators that can be used to formulate tailored strategies for individual countries.

Third, the exploration of condition-based patterns through decision tree.[26,27] Decision tree analysis is particularly effective for identifying conditional patterns in how specific SDG indicators influence GDP. It identifies combinations of SDG indicators that exert the greatest impact on GDP, offering detailed insights into the relationships among variables. This analysis provides actionable information essential for policy formulation, enabling the development of tailored strategies suited to the unique circumstances of each country.

Fourth, the capability for data-driven, sophisticated country classification and tailored strategy proposals. The machine learning techniques employed in this study enable data-driven and nuanced country classification that incorporates a wide range of SDG.[28,29] This approach provides a robust basis for formulating differentiated ODA strategies tailored to the characteristics of individual countries. Compared to traditional studies, the machine learning-based approach offers clear evidence for developing strategies specific to each country's needs.

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By deeply analyzing the patterns through which SDG indicators influence GDP per capita, this study overcomes the limitations of previous research and enables the formulation of more sophisticated, data-centric ODA strategies. Leveraging machine learning techniques, this study excels in identifying nonlinear relationships, uncovering condition-based patterns, and conducting data-driven country classifications, ultimately contributing to the establishment of concrete policy directions tailored to the unique characteristics of each country.

METHOD

This study leverages machine learning techniques to identify key SDG variables influencing the per capita GDP of 166.[30,31,32] The goal is to provide actionable insights for the formulation of tailored ODA strategies. The analysis uses country-specific scores for 17 SDGs from the 2023 SDGs Report as independent variables and GDP per capita as the dependent variable.

Scope of Analysis

The study targets 166 countries worldwide, encompassing both developed and developing nations. This broad scope allows for a comprehensive analysis of the economic, social, and environmental interactions reflected in the SDG indicators across countries. The primary focus is to contribute practically to ODA strategy formulation for developing countries.

Variables

1. Independent Variables: The 17 SDG scores provided in the 2023 SDGs Report are used as measures of SDG performance for each country. These indicators reflect various economic, social, and environmental factors, and exploring their influence on GDP per capita is a central objective of this research.
2. Dependent Variable: GDP per capita is set as the economic performance measure, allowing the study to analyze how country-specific SDG performance impacts economic growth and self-reliance.

Analysis Methods

This study employs a two-step analysis process, sequentially applying neural network analysis and decision tree analysis (using the CRT method), two prominent machine learning techniques.[33,34]

Step 1: Identifying Key Variables through Neural Network Analysis

Neural network analysis is first conducted to explore the nonlinear relationships between the 17 SDG indicators and GDP per capita. This method is particularly advantageous for detecting multidimensional and nonlinear patterns, enabling a comprehensive analysis of the complex impacts of SDG indicators on GDP. The analysis identifies the SDG indicators that have the most significant impact on GDP. These key variables are then selected for use in the subsequent decision tree analysis. The primary goal of neural network analysis is to understand the nonlinear influence of each SDG indicator on GDP, thereby constructing an optimal set of independent variables for decision tree analysis.[35]

Step 2: Exploring Patterns and Interactions through Decision Tree Analysis (CRT Method)

Using the key variables identified in the neural network analysis, decision tree analysis (specifically the CRT, or Classification and Regression Tree method) is applied. The CRT method is effective in uncovering conditional interaction patterns among major SDG indicators and their impact on GDP per capita. Decision tree analysis visualizes the conditional patterns, showing how combinations of specific SDG indicators influence GDP. This step predicts GDP levels based on country-specific SDG combinations and identifies critical areas requiring policy interventions. The primary objective of decision tree analysis is to derive conditional interaction formulas between SDGs and GDP, providing a concrete and tailored foundation for strategies that promote economic growth in developing countries.[36,37,38,39]

This two-step approach leverages the strengths of both methods: neural network analysis identifies significant variables, while decision tree analysis elucidates conditional patterns and relationships. Together, they enable the formulation of nuanced, data-driven ODA strategies tailored to the unique needs of individual countries.

RESULTS

Descriptive Statistics

The Sustainable Development Goals (SDGs), adopted by the United Nations General Assembly in 2015, represent a shared global agenda comprising 17 goals and 169 targets to be achieved by 2030. These goals aim to enhance economic, social, and environmental sustainability while addressing various global issues such as poverty eradication and human rights promotion. Below is a summary table outlining the 17 SDGs and their key details.

Table 1. Summary of the SDGs and Their Key Objectives

Goal	Objective
SDG 1	End poverty in all its forms everywhere
SDG 2	End hunger, achieve food security, and promote sustainable agriculture
SDG 3	Ensure healthy lives and promote well-being for all at all ages
SDG 4	Ensure inclusive and equitable quality education and promote lifelong learning opportunities
SDG 5	Achieve gender equality and empower all women and girls
SDG 6	Ensure availability and sustainable management of water and sanitation for all
SDG 7	Ensure access to affordable, reliable, sustainable, and modern energy for all
SDG 8	Promote sustained, inclusive, and sustainable economic growth, full and productive employment, and decent work for all
SDG 9	Build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation
SDG 10	Reduce inequality within and among countries
SDG 11	Make cities and human settlements inclusive, safe, resilient, and sustainable
SDG 12	Ensure sustainable consumption and production patterns
SDG 13	Take urgent action to combat climate change and its impacts
SDG 14	Conserve and sustainably use the oceans, seas, and marine resources for sustainable development
SDG 15	Protect, restore, and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt biodiversity loss
SDG 16	Promote peaceful and inclusive societies, provide access to justice for all, and build effective, accountable institutions
SDG 17	Strengthen the means of implementation and revitalize the global partnership for sustainable development

This foundational understanding of the SDGs serves as the basis for analyzing their impact on GDP per capita across 166 countries.

Table 2. Descriptive Statistics of Variables

	N	Minimum	Maximum	Mean	Std.
sdg1	151	0,00	100,00	75,2344	31,16995
sdg2	166	19,81	83,40	59,7991	10,62085
sdg3	166	12,95	97,12	69,6941	20,35458
sdg4	166	1,23	99,76	76,5130	23,18192
sdg5	166	13,05	94,02	63,2854	16,39969
sdg6	166	32,60	95,06	66,7107	14,09164
sdg7	166	8,70	99,55	61,4136	20,36435
sdg8	166	39,54	93,38	71,9529	10,59231
sdg9	166	1,65	99,13	51,6006	26,56168
sdg10	148	5,49	100,00	63,3430	26,94331
sdg11	166	13,83	99,86	72,1811	18,21553
sdg12	166	37,73	98,81	79,7759	16,09292
sdg13	165	1,29	99,93	82,6171	20,24282
sdg14	126	36,58	90,39	65,4950	11,47598
sdg15	166	26,48	97,85	66,6375	14,17560
sdg16	166	29,44	93,84	61,5464	15,51745
sdg17	166	29,35	94,03	60,9548	12,99186
GDP per capita	166	216,50	131034,10	16421,7133	23834,61062
Valid	106				

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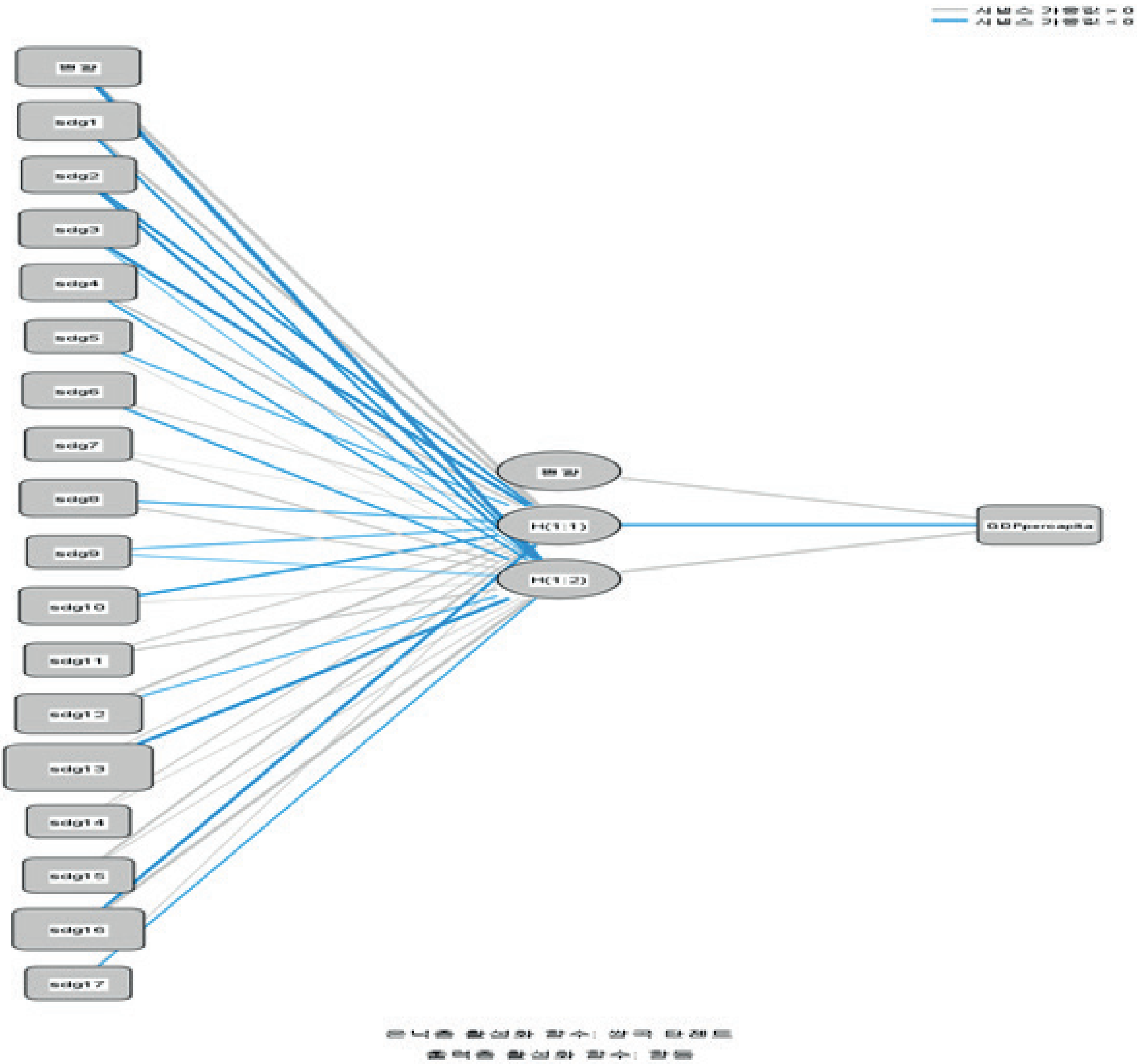
Neural Network Analysis Results

A neural network analysis was conducted with the 17 SDG variables as independent variables and GDP per capita as the dependent variable. Neural Network Analysis, a method in artificial intelligence and machine learning, mimics the structure of the human brain to learn and predict patterns in data. Key concepts include neurons, layers, weights, activation functions, and backpropagation. Neural networks use these components to interact and learn patterns from input data, enabling predictions on new data.

The diagram below visualizes the neural network analysis results, illustrating the relationships between each SDG indicator and GDP per capita.

- Input Layer: Represented by boxes labeled SDG1 through SDG17 on the left, these denote the SDG indicators fed into the neural network as independent variables. Each indicator independently influences the model as an input variable.
- Hidden Layers: Located in the middle are two hidden layer nodes (H(1:1), H(1:2)), which process the information received from the input layer and learn patterns. Each hidden layer node computes values using the inputs and their associated weights, applying an activation function. This enables the neural network to learn complex correlations.
- Connections (Arrows): The arrows indicate the connections between input variables and hidden layer nodes. Each connection is assigned a unique weight, reflecting its influence on the network's learning process.



Note: Hidden Layer Activation Function: Bipolar Tangent
Figure 1. Neural Network Structure Derived from Analysis Results

On the right side, GDP per capita represents the final prediction output of the neural network, synthesizing information from all input variables and hidden layers. The neural network learns how each SDG indicator impacts GDP per capita to produce this final prediction. This neural network structure serves as a model that analyzes and predicts the influence of each SDG indicator on GDP per capita. The hidden layers process the complex patterns from the input layer, ultimately estimating the value of GDP per capita.

The table below presents the results of the neural network analysis, showing the impact (weights) of each SDG indicator on the hidden layers and the output layer. These weights indicate how each indicator contributes to the final predicted value, GDP per capita.

In the hidden layers, H(1:1) and H(1:2) have bias values of 0,687 and -0,761, respectively. Bias is a constant that enhances the flexibility of the model, influencing the activation of the neural network. The output layer also includes a bias value of 0,426, which affects the model's final output value.

Table 3. Parameter Estimates

Predictor		**Prediction**		
		Hidden Layer 1		**Output Layer**
		H(1:1)	**H(1:2)**	**GDP per capita**
Input Layer	(Bias)	,687	-,761	
	sdg1	,432	-,249	
	sdg2	-,367	-,367	
	sdg3	-,485	-,021	
	sdg4	,310	-,195	
	sdg5	-,145	,002	
	sdg6	,155	-,270	
	sdg7	,014	,285	
	sdg8	-,247	,276	
	sdg9	-,155	-,109	
	sdg10	-,428	,105	
	sdg11	,202	,384	
	sdg12	,440	-,145	
	sdg13	,124	-1,022	
	sdg14	,132	,088	
	sdg15	,326	,094	
	sdg16	-,386	,458	
	sdg17	,039	-,126	
Hidden Layer 1	(Bias)			,426
	H(1:1)			-,643
	H(1:2)			,542

In summary, the variables that significantly influence GDP per capita in the table are the SDG indicators with high absolute weight values connected to the hidden layer nodes (H(1:1), H(1:2)). Specifically, since the weights connecting H(1:1) and H(1:2) to the output layer are -0,643 and 0,542, respectively, the SDG indicators linked to these hidden layer nodes can be considered crucial for GDP per capita.

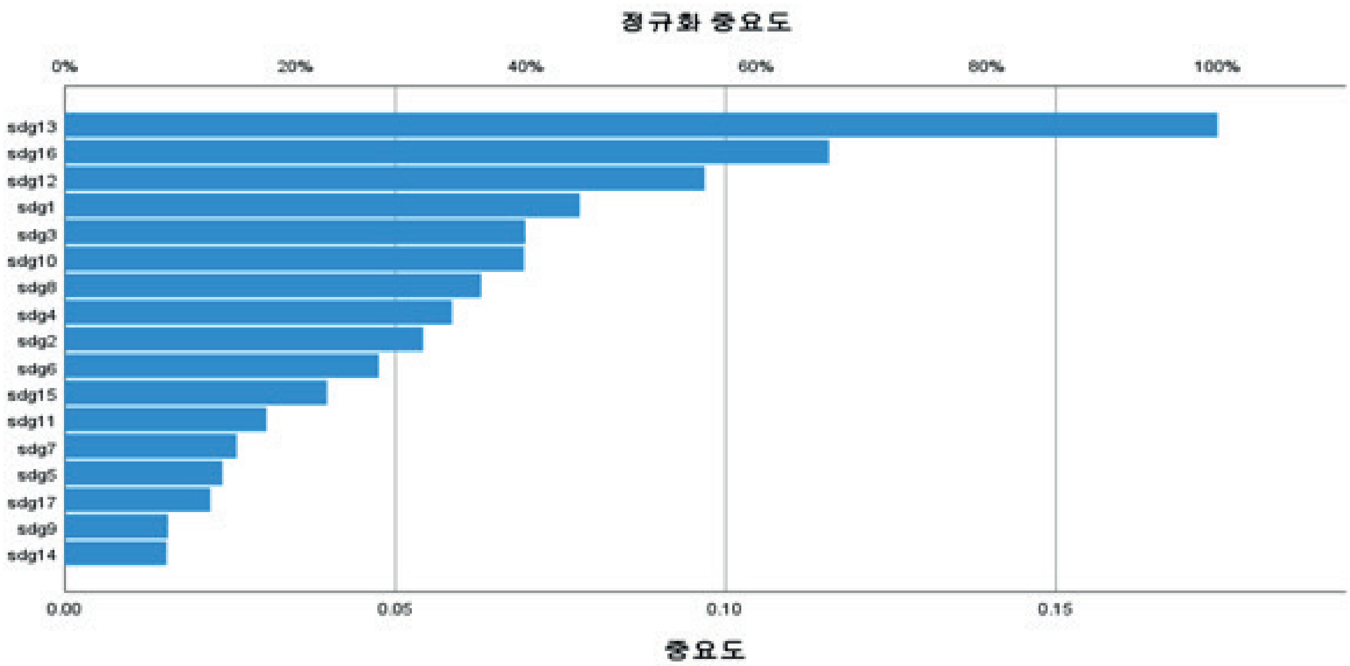
The table below illustrates the importance of the independent variables. Based on the "Importance" and "Normalized Importance" values of each indicator, it is possible to identify which SDG indicators have a significant impact on GDP per capita.

In the figure below, Importance represents the relative influence of each SDG indicator on GDP per capita as a numerical value. A higher value indicates that the corresponding SDG indicator has a greater impact on GDP per capita. Normalized Importance converts these importance values into percentages ranging from 0 % to 100 %.

Table 4. Importance of Independent Variables

	Weights	Normalized Weights
sdg1	0,078	44,6 %
sdg2	0,054	31,1 %
sdg3	0,070	39,9 %
sdg4	0,059	33,6 %
sdg5	0,024	13,6 %
sdg6	0,047	27,2 %
sdg7	0,026	14,9 %
sdg8	0,063	36,1 %
sdg9	0,016	8,9 %
sdg10	0,069	39,8 %
sdg11	0,030	17,5 %
sdg12	0,097	55,5 %
sdg13	0,174	100,0 %
sdg14	0,015	8,8 %
sdg15	0,040	22,7 %
sdg16	0,116	66,3 %
sdg17	0,022	12,6 %

The normalization is based on the variable with the greatest impact, SDG 13, which is set as the reference point (100 %), with the influence of the other variables displayed relative to it.



Note: The y-axis represents the SDG numbers, while the x-axis represents the importance (weights)
Figure 2. Normalized Importance of Independent Variables

As shown in the figure above, SDG 13 has a normalized importance of 100 %, making it the variable with the highest impact among all SDG indicators. This indicates that SDG 13 has a stronger relationship with GDP per capita compared to other variables. SDG 16, with a normalized importance of 66,3 %, is the second most influential variable, suggesting a significant correlation with GDP per capita.

SDG 1, SDG 3, and SDG 12 have normalized importance values of 44,6 %, 39,9 %, and 55,5 %, respectively, and are also considered relatively important variables influencing GDP per capita.

The graph visually represents the normalized importance of each variable. SDG 13 is shown as the longest bar, intuitively indicating its larger impact on GDP per capita compared to other SDG indicators. Following this, SDG 16, SDG 12, SDG 1, and SDG 3 appear as variables with relatively high influence.

Decision Tree Analysis Results

The figure below presents the results of the decision tree analysis performed using the top seven most important variables identified in the neural network analysis as independent variables.

The root node (topmost node) contains the entire dataset and displays basic statistics, such as the mean GDP per capita and variance. This node serves as the starting point for the subsequent classification process.

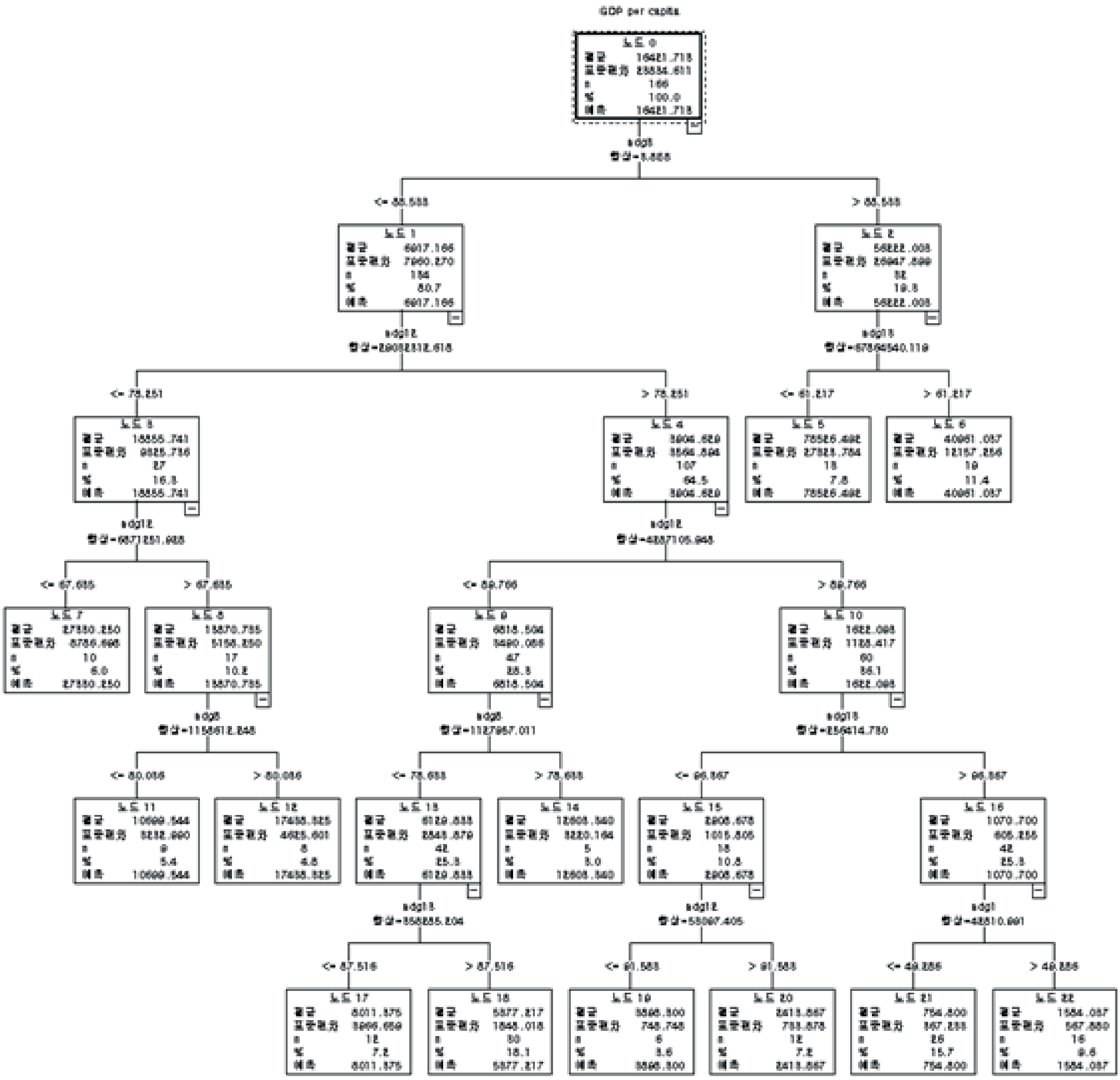


Figure 3. Decision Tree Analysis Results

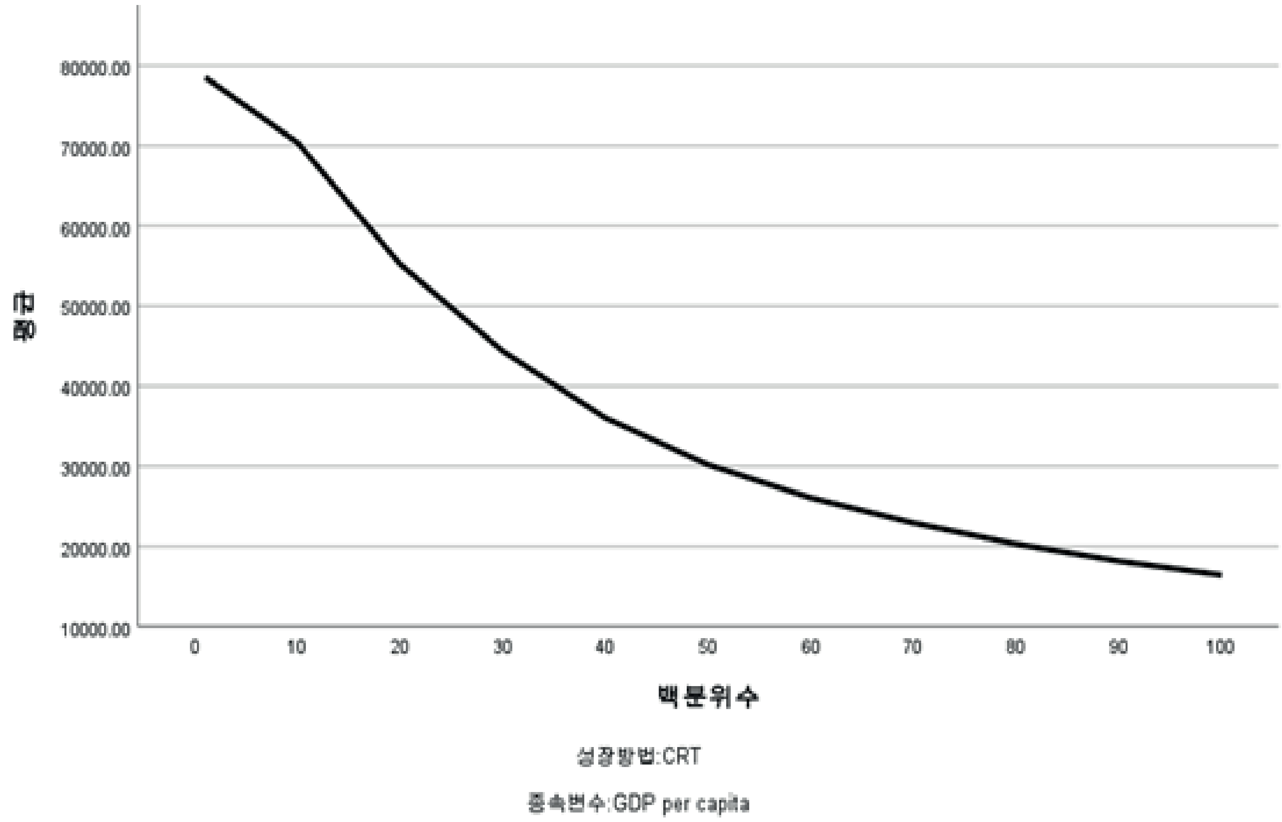
At each node, branching occurs based on specific SDG indicator values. For instance, the first split divides the data based on whether a certain SDG indicator value is less than or equal to 6 553 or exceeds it. These splits aim to more accurately predict GDP per capita by segmenting the data according to SDG indicator values.

The final nodes of each branch are leaf nodes, which display the mean GDP per capita and its corresponding variance for data satisfying the given conditions. A leaf node represents the predicted range of GDP per capita. For example, if a leaf node shows a GDP per capita value of 1 500, it means that the average GDP per capita for countries meeting those conditions is approximately 1 500.

This decision tree intuitively demonstrates how SDG indicators influence GDP per capita. The predicted GDP per capita varies based on SDG indicator values, allowing for a better understanding of the relative importance of each indicator. Branching conditions at higher-level nodes significantly impact GDP per capita predictions and can be used to classify high-income and low-income countries based on SDG indicator criteria.

Additionally, the figure below illustrates the distribution of GDP per capita across percentiles. The y-axis represents GDP per capita values corresponding to each percentile (ranging from 0 to 100). The graph shows a declining trend from the upper left to the lower right, indicating a decrease in GDP per capita as percentiles decrease.

This pattern suggests that countries in higher percentiles (wealthier countries) have higher GDP per capita, whereas countries in lower percentiles (low-income countries) have lower GDP per capita.



Note: the y-axis represents the average GDP per capita, while the x-axis denotes the percentiles.
Figure 4. Distribution of GDP Per Capita by Percentile

The graph visually represents the distribution of GDP per capita across countries, showing the economic disparity between high-income and low-income nations when segmented by percentiles. The significant difference in GDP per capita among higher-income countries indicates that a small number of wealthy nations significantly raise the overall average GDP per capita.

The table below summarizes the distribution and average GDP per capita of each group corresponding to the leaf nodes in the decision tree analysis. As shown, Node 5 and Node 6 have the highest average GDP per capita, at 78,526,4923 and 40,961,0588, respectively. This suggests that the conditions defining these groups likely correspond to countries with high GDP per capita.

Meanwhile, the average GDP per capita for Node 21 is 754,8000, indicating a very low level. This suggests that the conditions defining this group may be associated with countries that have low GDP per capita.

Among all the data, Node 13 accounts for the largest proportion at 18,1 %, with an average GDP per capita of 5 371,2167.

The countries included in each node are organized in the table 6.

Among the countries listed in the table, those classified as developing countries receiving aid primarily belong to groups below Node 11. Specifically, they are countries corresponding to Nodes 11, 17, 18, 19, 20, 22, and 21.

Table 5. Summary of Gains by Node

Node	N	Percent	Average (Unit: US Dollars)
5	13	7,8 %	78526,4923
6	19	11,4 %	40961,0368
7	10	6,0 %	27330,2500
12	8	4,8 %	17438,3250
14	5	3,0 %	12603,3400
11	9	5,4 %	10699,5444
17	12	7,2 %	8011,3750
18	30	18,1 %	5377,2167
19	6	3,6 %	3898,3000
20	12	7,2 %	2413,8667
22	16	9,6 %	1584,0375
21	26	15,7 %	754,8000

Growth Method: CRT
Dependent Variable: GDP per capita
Note: In decision tree analysis, growth methods refer to the algorithms or criteria used to determine how the tree expands or splits at each node. These methods dictate the rules for dividing the dataset into subsets based on specific variable thresholds.

Table 6. Country Classification by Node

	Countries	GDP Per capita (US Dollar)	Characteristics
Node 5	Denmark, Austria, Norway, Switzerland, Ireland, Belgium, Netherlands, Canada, Iceland, Luxembourg, United States, Australia, Singapore	78 526	SDG 3 is greater than 88 533 and SDG 13 is less than 61 217.
Node 6	Finland, Sweden, Germany, France, Czech Republic, Estonia, United Kingdom, Slovenia, Spain, Portugal, Japan, Italy, New Zealand, Greece, South Korea, Malta, Israel, Cyprus, Qatar	40 961	SDG 3 is greater than 88 533, and SDG 13 is greater than 61 217.
Node 7	Latvia, Lithuania, United Arab Emirates, Barbados, Saudi Arabia, Kuwait, Bahrain, Trinidad and Tobago, Bahamas	27 330	SDG 3 is less than 88 533, SDG 12 is less than 78 251, and SDG 12 is also less than 67 635.
Node 12	Poland, Croatia, Hungary, Slovakia, Chile, Uruguay, Bulgaria, Oman	17 438	SDG 3 is less than 88 533, SDG 12 is less than 78 251, and SDG 12 is greater than 67 635.
Node 14	Romania, Serbia, Cuba, Russia, China	12 603	SDG 3 is less than 88,533, SDG 12 is greater than 78 251 but less than 89 766, and SDG 3 is greater than 78 633.
Node 11	Belarus, Argentina, Costa Rica, Montenegro, Maldives, Malaysia, Mauritius, Panama, Mongolia	10 699	SDG 3 is less than 88 533, SDG 12 is less than 78 251 but greater than 67 635, and SDG 3 is less than 80 036.
Node 17	Ukraine, Thailand, Azerbaijan, Kazakhstan, Türkiye, Mexico, Iran, Turkmenistan, Lebanon, Guyana, Iraq, South Africa	8 011	SDG 3 is less than 88,533, SDG 12 is greater than 78 251 but less than 89 766, SDG 3 is less than 78 633, and SDG 13 is less than 87 516.
Node 18	Moldova, Georgia, Bosnia and Herzegovina, Brazil, Albania, Armenia, Fiji, Tunisia, North Macedonia, Bhutan, Dominican Republic, Peru, Algeria, El Salvador, Ecuador, Indonesia, Colombia, Jordan, Jamaica, Paraguay, Cabo Verde, Suriname, Nicaragua, Belize, Namibia, Gabon, Venezuela, Botswana, Eswatini, Djibouti	5 377	SDG 3 is less than 88 533, SDG 12 is greater than 78 251 but less than 89 766, SDG 3 is less than 78 633, and SDG 13 is greater than 87 516.
Node 19	Vietnam, Morocco, Egypt, Sri Lanka, Honduras, Guatemala	3 898	SDG 3 is less than 88 533, SDG 12 is greater than 78 251 and greater than 89 766, SDG 13 is less than 96 367, and SDG 12 is less than 91 583.

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Node 20	Kyrgyzstan, Uzbekistan, Bolivia, Philippines, Bangladesh, India, Laos, Zimbabwe, Papua New Guinea, Republic of Congo, Angola	2 413	SDG 3 is less than 88 533, SDG 12 is greater than 78 251, greater than 89 766, and greater than 91 583, while SDG 13 is less than 96 367.
Node 22	Tajikistan, Nepal, Côte d'Ivoire, Senegal, Ghana, Kenya, Myanmar, Pakistan, Gambia, Syria, Mauritania, Cameroon, Benin, Guinea, Nigeria, Comoros	1 584	SDG 3 is less than 88 533, SDG 12 is greater than 78 251 and greater than 89 766, SDG 13 is greater than 96 367, and SDG 1 is greater than 49 286.
Node 21	São Tomé and Príncipe, Rwanda, Mali, Tanzania, Malawi, Togo, Sierra Leone, Uganda, Lesotho, Ethiopia, Zambia, Burundi, Mozambique, Haiti, Burkina Faso, Madagascar, Liberia, Afghanistan, Democratic Republic of Congo, Sudan, Niger, Somalia, Yemen, Chad, Central African Republic, South Sudan	754	SDG 3 is less than 88 533, SDG 12 is greater than 78 251 and greater than 89 766, SDG 13 is greater than 96 367, and SDG 1 is less than 49 286.

CONCLUSION

As mentioned above, the analysis using the same indicators for both developed and developing countries reveals that developing countries predominantly belong to groups below Node 11. Specifically, they are classified under Nodes 11, 17, 18, 19, 20, 22, and 21, comprising 7 out of the total 12 nodes. Considering the characteristics of these countries, the following ODA strategy directions are proposed:

Node 11 Countries

SDG 3 is less than 88,533, SDG 12 is less than 78,251, SDG 12 is greater than 67,635, and SDG 3 is less than 80,036. Countries in Node 11 have intermediate capabilities in health, welfare, and sustainable consumption and production, indicating the need for targeted support to improve these areas. Therefore, an ODA strategy focusing on improving access to basic health services, introducing eco-friendly technologies, and enhancing resource efficiency is appropriate. This will help raise health standards and promote the sustainable use of resources.

Node 17 Countries

SDG 3 is less than 88,533, SDG 12 is greater than 78,251, SDG 12 is less than 89,766, SDG 3 is less than 78,633, and SDG 13 is less than 87,516. Countries in Node 17 exhibit moderate capabilities in health, sustainable production, and climate change adaptation, suggesting that further support is needed in these areas. Therefore, an ODA strategy focused on expanding basic health infrastructure, introducing eco-friendly production methods, and strengthening climate change resilience is appropriate. This will help these countries achieve more sustainable development and improve their capacity to adapt to environmental challenges.

Node 18 Countries

SDG 3 is less than 88,533, SDG 12 is greater than 78,251, SDG 12 is less than 89,766, SDG 3 is less than 78,633, and SDG 13 is greater than 87,516. Countries in Node 18 have relatively high capabilities in climate change adaptation, but improvements are needed in health services and resource-efficient consumption and production systems. Therefore, an ODA strategy should focus on expanding basic health services, introducing sustainable resource management and production methods, while also maintaining progress in climate change adaptation and strengthening their role as international leaders in this area. This approach will help these countries sustain their achievements and continue to lead in global climate action.

Node 19 Countries

SDG 3 is less than 88,533, SDG 12 is greater than 78,251 and greater than 89,766, SDG 13 is less than 96,367, and SDG 12 is less than 91,583. Countries in Node 19 have moderate capabilities in health services and climate change adaptation, but improvements can be made based on relatively well-established sustainable consumption and production systems. Therefore, an ODA strategy focusing on expanding health infrastructure, supporting sustainable consumption and production, and enhancing climate change resilience is appropriate. This will help improve health levels while promoting sustainable development.

Node 20 Countries

SDG 3 is less than 88,533, SDG 12 is greater than 78,251 and greater than 89,766, SDG 13 is less than 96,367, and SDG 12 is greater than 91,583. Countries in Node 20 have already established robust sustainable consumption and production systems; however, additional support is needed in health services and climate change adaptation. Therefore, an ODA strategy focusing on enhancing access to health services, maintaining sustainable resource management systems, and expanding climate change adaptation capacities is appropriate. This approach will help improve both health outcomes and environmental sustainability simultaneously.

Node 22 Countries

SDG 3 is less than 88,533, SDG 12 is greater than 78,251 and greater than 89,766, SDG 13 is greater than 96,367, and SDG 1 is greater than 49,286. Countries in Node 22 have relatively good performance in poverty alleviation and climate change adaptation. However, they require intensive support to improve access to health services and maintain sustainable consumption and production systems. Therefore, an ODA strategy focusing on expanding health infrastructure, strengthening sustainable consumption and production systems, maintaining climate change resilience, and continuing efforts to alleviate poverty is appropriate. This approach will promote sustainable development across the country.

Node 21 Countries

SDG 3 is less than 88,533, SDG 12 is greater than 78,251 and greater than 89,766, SDG 13 is greater than 96,367, and SDG 1 is less than 49,286. Countries in Node 21 have relatively good performance in climate change adaptation and sustainable production systems, but improvements are needed in poverty reduction and health levels. Therefore, an ODA strategy focused on enhancing access to health services, expanding poverty reduction programs, maintaining sustainable consumption and production systems, and sustaining climate change adaptation capabilities is suitable. This strategy will contribute to fostering sustainable development across the country.

REFERENCES

1. Alesina A, Dollar D. Who gives foreign aid to whom and why? Journal of Economic Growth. 2000; 5(1): 33-63. Available from: https://doi.org/10.1023/A:1009874203400

2. Bourguignon F, Sundberg M. Aid effectiveness: Opening the black box. American Economic Review. 2007; 97(2): 316-321. Available from: https://doi.org/10.1257/aer.97.2.316

3. Burnside C, Dollar D. Aid, policies, and growth. American Economic Review. 2000; 90(4): 847-868. Available from: https://doi.org/10.1257/aer.90.4.847

4. Brown L, Lee H. Enhancing SDG alignment in developing countries through machine learning classification. Development Policy and Analytics. 2022; 34(2): 312-329.

5. Clemens MA, Radelet S, Bhavnani RR. Counting chickens when they hatch: The short-term effect of aid on growth. Center for Global Development Working Paper. 2004; 44.

6. Collier P, Dollar D. Aid allocation and poverty reduction. European Economic Review. 2002; 46(8): 1475-1500. Available from: https://doi.org/10.1016/S0014-2921(01)00187-8

7. Choi Y-C. Application of Methodology for Measuring Effectiveness in Official Development Assistance (ODA). Korean Comparative Government Review. 2019; 23(4): 1-27.

8. Jang J-H. Exploring Feedback Loops for Enhancing Educational Competitiveness and Policy Simulation. Social Economy and Policy Studies. 2017; 7(3): 109-144.

9. Kato H. Japan’s ODA to Africa: Characteristics and Challenges. JICA Research Institute. 2016.

10. Arase D. Japan’s ODA Policy in Transition: Major Influences, New Directions and Future Prospects. Asia Program Special Report, Woodrow Wilson International Center for Scholars. 2005.

11. SIDA. Sweden’s Development Cooperation Policy: An Overview. Swedish International Development Cooperation Agency (Sida); 2017.

12.Nilsson A. Swedish Aid Policy: Context, Lessons and Challenges. Expert Group for Aid Studies (EBA); 2014.

13. BMZ. Germany’s Development Policy: A Policy for the Future. Federal Ministry for Economic Cooperation and Development (BMZ). 2014.

14. GIZ. German Development Cooperation: Principles and Goals. Deutsche Gesellschaft für Internationale

Zusammenarbeit (GIZ). 2015.

15. Hansen H, Tarp F. Aid and growth regressions. Journal of Development Economics. 2001; 64(2): 547-570. Available from: https://doi.org/10.1016/S0304-3878(00)00150-4.

16. Sachs JD. The end of poverty: Economic possibilities for our time. Penguin Press; 2005.

17. Easterly W, Pfutze T. Where does the money go? Best and worst practices in foreign aid. Journal of Economic Perspectives. 2008; 22(2): 29-52. Available from: https://doi.org/10.1257/jep.22.2.29

18. Craven MW, Shavlik JW. Using neural networks for data mining. Future Generation Computer Systems. 1997; 13(2-3): 211-229.

19. Quinlan JR. C4.5: Programs for Machine Learning. San Mateo (CA): Morgan Kaufmann; 1993.

20. Smith J, Lee S. A machine learning approach to assessing development aid needs. Journal of Policy Studies. 2020; 54(1): 98-115.

21. Ahmed S, Khan A. Machine learning for ODA strategy formation: Clustering developing nations. World Development Policy Journal. 2021; 38(3): 89-107.

22. Chen T, Guestrin C. XGBoost: A scalable tree boosting system. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. 2016; 785-794.

23. Zhang GP. Neural networks for classification: A survey. IEEE Trans Syst Man Cybern C Appl Rev. 2000; 30(4): 451-462.

24. Tanaka Y, Lee J. Machine learning techniques for sustainable development classification: A case study of low-income nations. Journal of Global Policy. 2021; 15(1): 48-65.

25. Zhao F, Li W. Data-driven classification of developing nations: Implications for aid allocation. World Development Journal. 2020; 96(2): 301-319.

26. Gupta R, Patel S. Clustering and classification of SDG data using machine learning algorithms. Journal of Development Analytics. 2021; 6(4): 377-392.

27. Ahmad N, Khan M. Decision tree applications in developing country classification for ODA. International Development Insights. 2022; 41(2): 101-119.

28. Brown A, Park E. Enhancing aid distribution with machine learning: A study on SDG-based clustering. Journal of Development Economics. 2020; 47(1): 103-118.

29. Huang X, Zhang Y. Machine learning methods in country classification for sustainable development. Development Journal. 2022; 16(2): 157-171.

30. Smith T, Brown R. Machine learning applications for ODA allocation: A case study of sub-Saharan Africa. Journal of International Development. 2019; 34(2): 214-227.

31. Chen L, Zhou X. Using neural networks for classification of countries based on SDG indicators. Journal of Development Policy Studies. 2018; 23(2): 178-192.

32. Reddy V, Singh P. Applying machine learning in international aid strategies: A framework for classification and prediction. Global Development Journal, 2021; 29(1): 44-62.

33. Mitchell TM. Machine Learning. New York: McGraw-Hill; 1997. Chapter: Decision trees and neural networks.

34. Rumelhart DE, Hinton GE, Williams RJ. Learning representations by back-propagating errors. Nature. 1986; 323(6088): 533-536.

35. Bishop CM. Neural Networks for Pattern Recognition. Oxford: Oxford University Press; 1995.

36. Fadare SA, Gulanes AA, Torres JD la C, Guiao EMN, Tagaylo JP. Enhancing Physical Activity Through Information Technology: Current Trends and Future Directions. Salud, Ciencia y Tecnología. 2024;4:950.

37. Sun H, Caluyo F, De Ocampo AL, Hernandez R, Sarmiento J. Urban energy management system based on intelligent linker. Salud, Ciencia y Tecnología. 2024;4:.915.

38. Quinlan JR. Induction of decision trees. Machine Learning. 1986; 1(1): 81-106.

39. Safavian SR, Landgrebe D. A survey of decision tree classifier methodology. IEEE Trans Syst Man Cybern. 1991; 21(3): 660-674.

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