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A Hybrid MOO, MCGDM, and Sentiment Analysis Methodologies for Enhancing Regional Expansion Planning: A Case Study Luwu - Indonesia

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Abstract
The study introduces a new framework integrating Multi Objective Optimization (MOO), Multi Criteria Group Decision Making (MCGDM), and sentiment analysis to improve regional expansion planning, particularly in developing countries. The framework addresses challenges such as governance, resource allocation, and public inclusion, aiming to make decision-making more transparent and adaptive. The study involves government agencies, experts, and communities using relevant variables. The model integrated 12 factors and 27 criteria within the MOO, encompassing 5 regions and 25 subdistricts in the MCGDM. Additionally, it analyzed 900 citizen comments through sentiment analysis and employed 9 indicators from 15 regions. The results demonstrated high accuracy, achieving a score of 0.98. The study demonstrates that the hybrid approach optimizes planning by balancing technical criteria and public sentiment, leading to more inclusive outcomes. The study lays a solid foundation for future research and practical application, making valuable contributions to the field of decision science, regional planning, and beyond.

Keywords- MOO, MCGDM, Machine learning, Sentiment analysis, Region expansion.

1. Introduction

Regional spatial planning is the main instrument to optimize production, life, and environmental space utilization, significantly impacting social, economic, and environmental sustainability. Research by Hou et al. (2022) stated that developing countries like China, India, and Indonesia have rapidly adopted regional expansion policies driven by government efforts to decentralize resource management and foster local economic growth. However, these policies have sometimes failed due to conflicts of interest that undermine democratic processes, leading to decentralized power systems in autonomous regions and making it difficult to achieve welfare goals (Montecinos, 2020; Saputra, 2021). For instance, tensions between regional nationalists, the central government, and immigrant workers in Catalonia, Spain, triggered a pro-independence movement, revealing the challenges of territorial division based solely on legal frameworks (Djen and Qodir, 2023).

To mitigate these challenges, Fu et al. (2022) argue that effective regional development necessitates a comprehensive approach that accounts not only for legal considerations but also for the needs of local communities, economic potential, and geographical and social contexts. This study aims to address these challenges by proposing a multi objective optimization and multi criteria group decision making framework for regional expansion planning. The objectives include optimizing criteria for regional development, building a decision-making model using MOO integrated with MCGDM, and developing a sentiment analysis-based model to gauge public opinion on regional expansion. These objectives prioritize democratic participation, involving both stakeholders and the community in decision-making processes.

Technological advances are crucial in achieving sustainable development goals, as they enable more inclusive and representative decision-making. Decision Support Systems (DSS) can process complex data and facilitate informed decision-making in regional planning, as demonstrated by previous research (Faisal et al., 2024). For instance, MCGDM models have been used to set regional development priorities (Setiyowati et al., 2019) optimize site selection (Djelloul and Hamdadou, 2023), and improve infrastructure planning, such as water resources recovery (Južnič-Zonta et al., 2022). Research also shows written discussions mediated by information and communication technology (ICT) are more effective than direct discussions in decision-making processes (Gusakova and Romanova, 2019).

In managing regions, a holistic approach is essential (Creighton et al., 2021). MCGDM methods have been applied to prioritize strategies for regional development (Gayen et al., 2024) and analyze the feasibility of regional expansion, which involves numerous criteria and complex data. The effectiveness of survey-based methodologies relies on the assumption that the questions can accurately capture the key criteria and perspectives involved (Faisal and Rahman, 2023b).

Optimization models offer multiple solutions by using different combinations of decision variables (Chen and Zheng, 2021). Research by Santos et al. (2019) highlighted the use of multi-criteria decision analysis in DSS to assess sustainability, moreover Chen and Zheng (2021) expanded on this with a multi-object optimization model for intelligent decision-making. Similarly, Chen et al. (2022) developed an integrated MOO-DSS system for highway agencies to find optimal planning strategies. This study proposes a machine learning framework by integrating MOO-MCGDM as a supporting tool for determining regional expansion decisions by involving elements of government, experts, and communities and using relevant variables as measuring tools. Research gaps related to MOO and MCGDM are summarized in **Table 1**.

Table 1. Research gap summary.

No.	References	Objective	Methodology
1.	Seddiki et al. (2016)	Thermal renovation of masonry buildings	PROMETHEE and GAIA
2.	Liou et al. (2018)	Aerotropolis case	DEMATEL + FDANP + FVIKOR
3.	Lotti and Caetano (2018)	Airport for cargo selection	AHP + Paretto
4.	Shojaei et al. (2018)	Performance evaluation and ranking	VIKOR + Taguchi Loss Function + BWM
5.	Dožić (2019)	Aviation industry	TOPSIS + FTOPSIS + DEMATEL
6.	Yan'gang and Zheng (2019)	Satellite cabin layout	CCSD + Paretto
7.	Lu et al. (2020)	Water Quality Monitoring System (WQMS)	MCGDM with dual hesitant fuzzy (DHF)
8.	Meng et al. (2021)	Energy systems optimization	NSGA-II algorithm
9.	Guo et al. (2022)	Distributed Energy Systems (DES)	Entropy + TOPSIS
10.	Chen et al. (2022)	The management of rehabilitation and large-scale network pavement maintenance	NSGA-II + Pareto-Front
11.	Ziemba and Gago (2022)	Determine which cars of this kind are most beneficial from the viewpoints of the VSS's owner and a prospective client	PROSA MCGDM + PROMETHEE + MCGDM
12.	Farid and Donyatalab (2022)	Optimal selecting of sanitarium sites for COVID-19 Patients	ELECTRE-VIKOR and q-ROFSs
13.	Smedberg and Bandaru (2023)	Performance optimization problem	NSGA-II
14.	Nallolla et al. (2023)	Combining renewable energy sources (RES) with a hybrid microgrid	MOGWO + MOPSO
15.	Neira-Rodado et al. (2023)	Improve decision-making	Apripori + Topsis + Paretto
16.	Mahmoodi et al. (2024)	Industry 4.0 and smart manufacturing	SBBA + NSGA-II + DE
17.	Faisal et al. (2024)	Proposed a framework for regional expansion planning	Fuzzy Delphi + Rank Reciprocal + MABAC + BORDA + Naïve Bayes + FKNN

This study builds on these advancements by proposing a machine-learning framework integrating MOO and MCGDM for regional expansion decision-making. This framework ensures that key variables such as economic stability, governance, and public safety are incorporated by involving governments, experts, and communities in a transparent and inclusive process. The proposed methodology is adaptable to the unique contexts of developing countries, where regional expansion policies must account for complex socio-economic and governance challenges. Integrating MOO, MCGDM, and sentiment analysis offers a more flexible, inclusive, and effective approach to regional planning.

2. Methodology

2.1 Multi Criteria Group Decision Making

Multi Criteria Group Decision Making makes it easy for participants to express their opinions and achieve the best computer solution, where the implementation of a decision-making process involves a group of people collaborating in choosing one or more alternatives to solve a particular problem (Carneiro et al., 2021). In this study, the MCGDM model obtains a representative value for assessing all alternatives or regions in an area that proposes expansion. The assessment is based on criteria obtained from a collection of variables related to the feasibility of regional expansion.

The MCGDM model includes key factors such as resource availability, economic stability, environmental sustainability, innovation and technology, and governance. These factors are critical in assessing the feasibility and priorities of regional development, providing a holistic view of the potential impacts of regional expansion. An illustration of the application of the MCGDM model is shown in **Figure 1**.

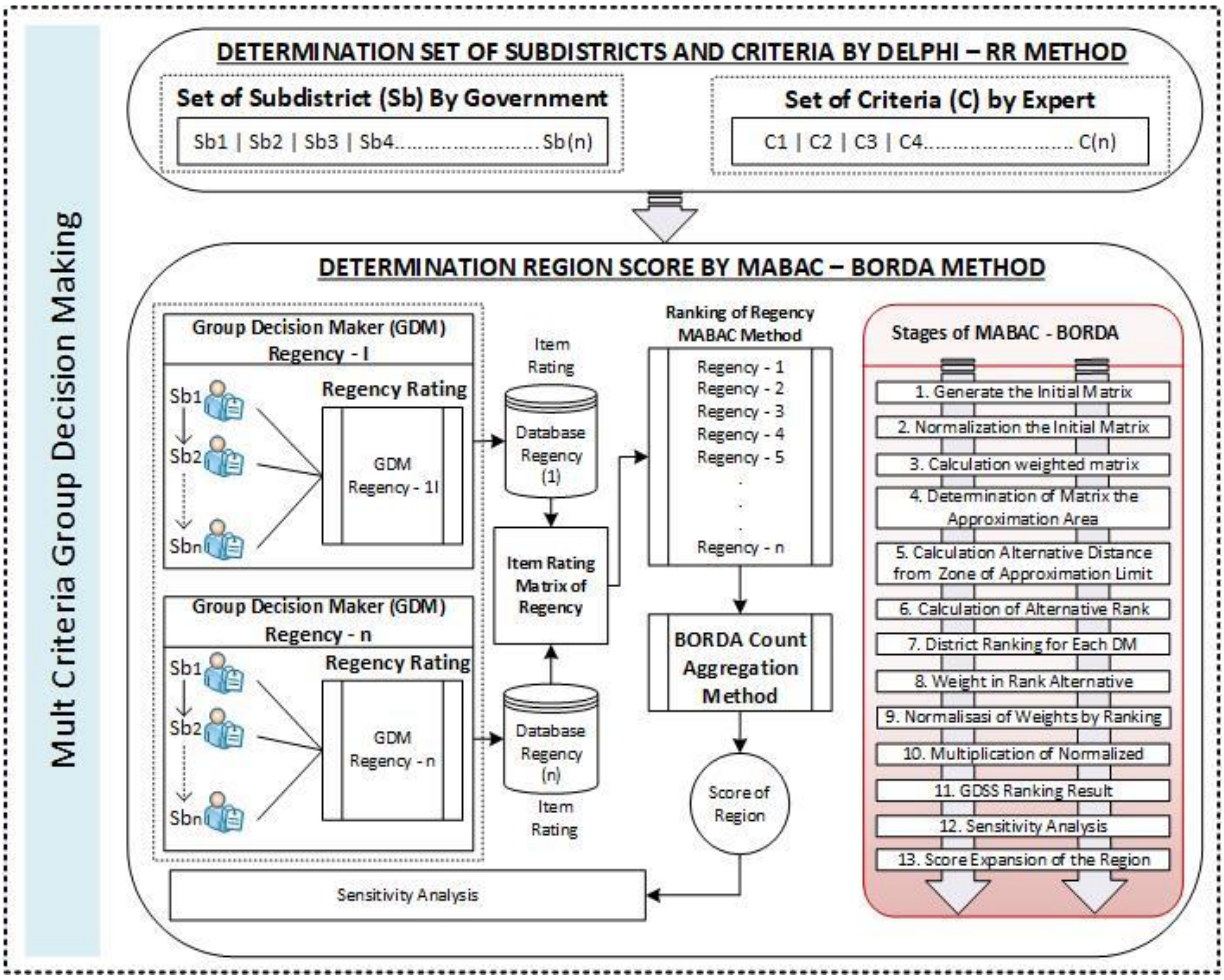

Figure 1. Proposed MCGDM for determination of region score.

2.2 Multi Objective Optimization Fuzzy Delphi - Rank Reciprocal - MABAC - BORDA

Operations research specialities such as Multi Objective Optimization and Multi Criteria Decision Making seek to assist in reaching the best judgments possible in challenging situations (Neira-Rodado et al., 2023). The rank reciprocal method computes the magnitude of the weight values while accounting for the varied significance of the indices order (Faisal and Rahman, 2023b).

Given that insufficient or inaccurate information frequently impedes decision-making processes, the Fuzzy Delphi Method (FDM) provides a robust framework for handling uncertainties and ambiguities (Mohammed et al., 2022). By applying criteria different from conventional quality performance metrics, Convergence and the diversity of non-dominated solutions are compared to determine how effective the FDM approach is. The threshold is determined by Equation (1).

$$d(\bar{m},\bar{n}) \ = \sqrt{\frac{1}{3} * [\,(m1 + m2 + m3)]} \qquad (1)$$

where, $d(\bar{m}, \bar{n})$ represents the distance or difference being calculated between two sets of values, $\bar{m}$ and $\bar{n}$. Variable of $m1, m2, m3$ are the individual components of the set $\bar{m}$. The formula sums up these

components. If $\bar{n}$ is involved, it is implied that the difference between the corresponding components from $\bar{m}$ and $\bar{n}$ might be considered but is not explicit in the formula. The 1/3 value is a normalization factor, indicating that the components' sum is being averaged (dividing by 3 because there are three components, m_1, m_2, m_3). To establish a threshold value (d), the dataset makes use of triangular fuzzy numbers. It is necessary that the threshold value (d) meet the requirement of being less than or equal to 0.2. The aggregate calculation process is a fuzzy evaluation method that determines the value of the fuzzy score using Equation (2):

$$\tilde{A} = \left(\frac{1}{n}\sum_{i=1}^{n} l_i, \frac{1}{n}\sum_{i=1}^{n} m_i, \frac{1}{n}\sum_{i=1}^{n} u_i\right) \quad (2)$$

where, "n" is the number of experts. Variable "l", "m", and "u" are the aggregated lower bound, middle bound, and upper bound, respectively.

Since the objective judgment of a group of specialists is always of higher quality than the opinion of a single person, the fuzzy Delphi method enables research to function autonomously, adapt its dynamics to research objectives, and make strategic decisions.

The Rank Reciprocal (RR) method is calculated using the following Equation (3):

$$w_i = \frac{\frac{1}{r_i}}{R} = \frac{\frac{1}{r_i}}{\sum_{i=1}^{n}\frac{1}{r_i}} \quad (3)$$

where, $\boldsymbol{r_i}$: the rank of the i-th criterion, $\frac{\mathbf{1}}{\boldsymbol{r_i}}$: the reciprocal of the rank, reflecting relative importance, $\boldsymbol{n}$: the number criteria, $\sum_{i=1}^{n}\frac{1}{r_i}$ or $\boldsymbol{R}$: the sum of all reciprocals, $\boldsymbol{w_i}$: the normalized weight of the i-th criterion.

Following the weighting of each criterion, the process is then used for the Multi Attributive Border Approximation Area Comparison (MABAC) approach, which is developed using the subsequent phases (Chakraborty et al., 2023):

Step 1. Formation of the initial decision matrix (X). The first step is to evaluate "m" alternatives according to "n" criteria, which the alternatives in the form of vectors $A_i = (x_{i1}, x_{i2}, \ldots, x_{in})$, where x_{ij} is the value of the "i-th" alternative according to the "*j-th*" criterion ($i = 1,2,\ldots,m$; $j = 1,2,\ldots,n$), and determined using Equation (4).

$$X = \begin{array}{c} \\ A_1 \\ A_2 \\ \ldots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1n} \\ x_{21} & x_{22} & \ldots & x_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ x_{m1} & x_{m2} & \ldots & x_{mn} \end{bmatrix} \end{array} \quad (4)$$

Step 2. Normalization of the elements from the initial matrix (X) using Equation (5):

$$N = \begin{array}{c} \\ A_1 \\ A_2 \\ \ldots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\ \begin{bmatrix} t_{11} & t_{12} & \ldots & t_{1n} \\ t_{21} & t_{22} & \ldots & t_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ t_{m1} & t_{m2} & \ldots & t_{mn} \end{bmatrix} \end{array} \quad (5)$$

where, the elements of the normalized matrix (N) are determined using the Equations (6) and (7).

The criteria for benefit type are written as follows:

$$t_{ij} = \frac{x_{ij} - x_i^-}{x_i^+ - x_i^-} \quad (6)$$

The criteria for cost type are written as follows:

$$t_{ij} = \frac{x_{ij} - x_i^+}{x_i^- - x_i^+} \quad (7)$$

Notations x^+ indicates benefit type criteria as higher value preferred, while notations x^- indicates cost type criteria as lower value preferred. The notations to determine the normalization of the initial decision matrix.

Step 3. Calculation of the elements from the weighted matrix (V) by Equation (8):

$$v_{ij} = fw_i t_{ij} + fw_i \quad (8)$$

where, t_{ij} are the elements of the normalized matrix (*N*), fw_i is the weight coefficients of the factor and criteria.

Step 4. Determination of the border approximation area matrix "G" for each criterion using Equation (9):

$$g_i = \left(\prod_{j=1}^{m} v_{ij}\right)^{1/m} \quad (9)$$

Step 5. Calculation of the distance alternative from the border approximation area for the matrix elements (Q) using Equation (10):

$$Q = V - G \quad (10)$$

Step 6. Ranking the alternatives using Equation (11):

$$S_i = \sum_{j=1}^{n} q_{ij}\ , j=1,2,..,n,\ i=1,2,..,m \quad (11)$$

where, "n" is the number of criteria, and "m" is the number of alternatives listed.

The final stage of Multi Objective Optimization is calculating alternative solutions using the Bremen Overseas Research and Development Association (BORDA) (Ahmadi and Herdiawan, 2021). The BORDA score for an agent $i \in N$ of an alternative x is $Bi\ x \equiv \#\{y \in A | x \succ i\ y\}$ and the BORDA score of an alternative x is $Bx \equiv \sum n\ i = 1Bi\ x$. An alternative in "$A$" that has the highest BORDA score among all the alternatives is referred to as a BORDA winner, and an alternative with the lowest BORDA score among all the alternatives is referred to as a BORDA loser (Moreno and Salmaso, 2024).

2.3 Sentiment Analysis Using Naïve Bayes

Sentiment analysis generates useful information for users to aid decision-making (Shaheen et al., 2023). Sentiment analysis can be used to assist governments in adjusting, modifying, or reformulating policies in order to increase public acceptance. Naïve Bayes has a high degree of accuracy in classifying sentiment analysis (Fitri et al., 2019), as explained in Equation (12):

$$P(A \mid B) = \frac{P(B|A)\ P(A)}{P(B)} \quad (12)$$

Furthermore, at the time of classification, the algorithm will find the highest probability of all categories of comments tested using Equation (13):

$$Vmap = argmax\ vj \in VP\ (vj) \prod P(ai \mid vj) \quad (13)$$

The probability of occurrence of a certain category *P(vj)* from a set of entered can be calculated using the Equation (14):

$$P(vj) = \frac{|\ doc\ j\ |}{|training|} \quad (14)$$

The probability of a word showing a tendency to a certain category in a text is calculated by Equation (15):

$$P(ai \mid vj) = \frac{|\ ni+1\ |}{|\ n+word\ |} \quad (15)$$

2.4 Classification Using Fuzzy K-Nearest Neighbors

Fuzzy K-Nearest Neighbors (FKNN) is a classification method that combines fuzzy techniques with the KNN classifier, which is done by assigning class membership values to test data to predict using membership degree values in each class. A supervised machine learning approach called fuzzy K-Nearest Neighbors works well for regression and multiclass classification (Adhikary and Banerjee, 2023). The Fuzzy KNN is described using Equation (16) as follows (Vommi and Battula, 2023):

$$u_i(x) = \frac{\sum_{j=1}^{K} u_{ij}(1\ /\ ||\ x-u_i||\ \frac{2}{m-1}}{\sum_{j=1}^{K}(1\ /\ ||\ x-u_i||\ \frac{2}{m-1}} \quad (16)$$

Finally, choose the class using Equation (17):

$$y' = ArgMax_{j=1}^{C}(u(x_i, x_i)) \quad (17)$$

2.5 Proposed Framework

The framework developed in this study seeks to optimize the regional expansion planning process by employing Multi Objective Optimization techniques alongside group decision support systems. This approach aims to enhance the efficiency, effectiveness, and quality of decision-making in the context of information technology-based regional planning. While the framework is designed with flexibility to accommodate diverse regional contexts beyond Indonesia, certain modifications are necessary. These include adjusting criteria and weights according to local conditions and integrating region-specific data sources to ensure both accuracy and contextual relevance. The design of the framework is presented in **Figure 2**.

The proposed machine learning framework offers a significant contribution by providing a structured, multi criteria group decision-making approach to regional expansion that integrates stakeholder perspectives. This is particularly beneficial for developing countries, where regional planning is frequently hindered by challenges such as limited resource allocation, political instability, and public discontent. By incorporating local conditions and public sentiment into the decision-making process, the framework facilitates more informed, transparent, and democratic regional expansion planning.

The proposed framework integrates various technological advancements, such as machine learning algorithms, Naïve Bayes classification, Fuzzy K-Nearest Neighbors, and sentiment analysis tools. By employing these technologies, the framework enhances stakeholder engagement through increased transparency and inclusivity in decision-making, ultimately fostering more robust democratic participation.

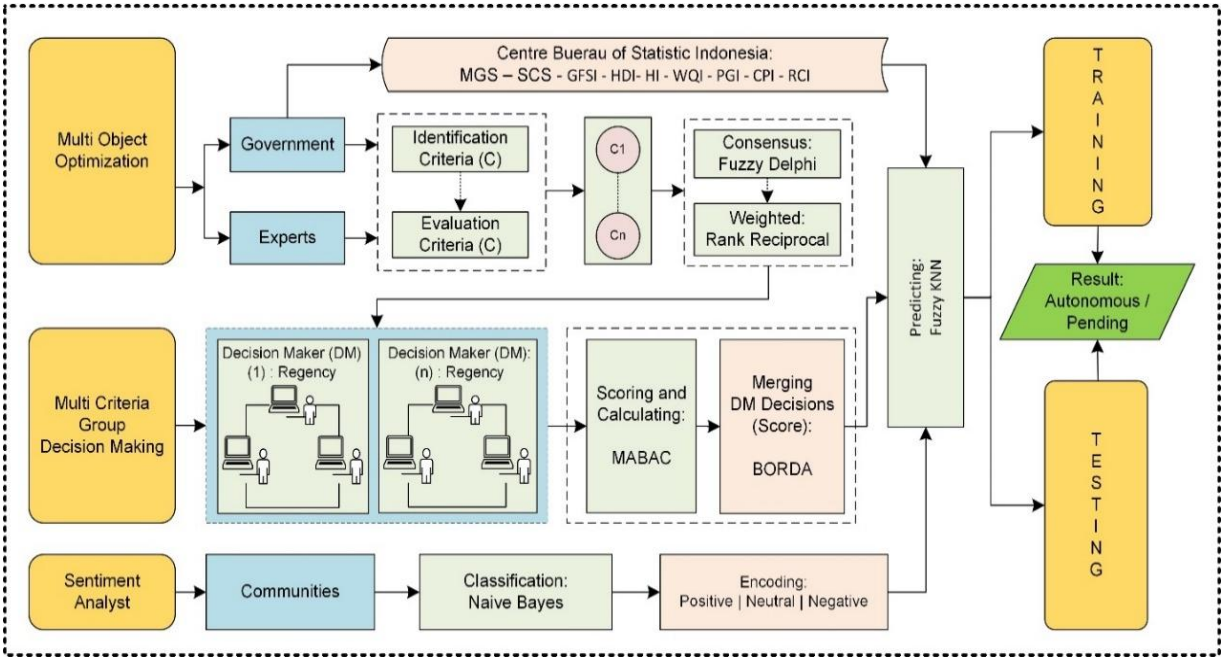

Figure 2. Proposed framework.

3. Illustrative By Case Study

3.1. Evaluation of Criteria

The cornerstone of effective survey-based research is crafting questions capable of precisely portraying the participants' practices, conditions, experiences, individual traits, or viewpoints (Einola and Alvesson, 2021). In order to obtain information for the purpose of creating a questionnaire, interviews were therefore done with a variety of sources, such as village chiefs, local governments, and experts in regional development planning. Asking questions is a crucial part of the learning process and is fundamentally integrated into critical thinking (Friston et al., 2020). We decided to select the variables and criteria from the Central Bureau of Statistics (CBS) of Indonesia based on their consistency, standardization, and relevance to the specific context of the framework and data accuracy, where CBS of Indonesia is a leading institution that provides comprehensive and reliable statistical data that reflects the socio-economic conditions of Indonesia.

The criteria evaluation technique employed by experts in regional expansion is a systematic process designed to assess various relevant aspects of the regional expansion plan or proposal. The technological prerequisites for the creation of new regions must include the elements that serve as the foundation for those regions' formation, such as economic capacity, regional potential, sociocultural and sociopolitical aspects, population density, area, defence-security, and other elements that facilitate the implementation of regional expansion (Souza et al., 2023; Saputra, 2021). This study used the criteria used by previous studies, as shown in **Table 2**.

Table 2. The variable for assessment of region expansion.

No.	Factor	Criteria
1.	Resource availability (A)	Skilled labor (A1), natural resources (A2), and technological infrastructure (A3)
2.	Economic stability (B)	Growth trends (B1), inflation rates (B2), and currency stability (B3)
3.	Environmental sustainability (C)	Environmental initiatives (C1), policies (C2), competitive landscape (C3)
4.	Innovation and technology (D)	Local innovation ecosystems (D1) and digital infrastructure (D2)
5.	Cultural diversity (E)	Demographic makeup (E1), cultural heritage (E2), and diversity (E3)
6.	Social cohesion (F)	Community engagement (F1), social inclusion (F2), and consumer behaviors (F3)
7.	Governance and stability (G)	Political environment (G1) and governance structures (G2)
8.	Security situation (H)	Crime rates (H1), internal security (H2), and law enforcement (H3)
9.	Demographics education (I)	Age distribution (I1), population growth (I2), urbanization(I3), education (I4), literacy rate (I5)
10.	Land use and availability (J)	Rural distribution (J1) and land for development (J2)
11.	Environmental factors (K)	Climate (K1), natural disasters (K2), and environmental risks (K3)
12.	Public safety (L)	Policing (L1), emergency services (L2), disaster preparedness (L3), and data protection (L4)
13.	Cybersecurity (M)	Digital infrastructure (M1) and border control (M2)

Table 3. Triangular fuzzy numbers (TFNs) of five-point likert scale.

Linguistic terms	Score	Corresponding TFNs		
Very agree	5	0.6	0.8	1
Agree	4	0.4	0.6	0.8
Moderately agree	3	0.2	0.4	0.6
Disagree	2	0	0.2	0.4
Very disagree	1	0	0	0.2

Based on the data in **Table 2**, the first stage of the evaluation was carried out by experts to select the relevant variables used according to the provisions of the FDM score < threshold (δ = 0.2). The importance of attribute *"j"* is evaluated by expert *"I"* as "v" = (x_{ij} ; y_{ij} ; z_{ij}), I = 1,2,3….,n; J = 1,2,3,..m; furthermore, weight *"v_j"* of element *"j"* is v_j = (x_{ij} ; y_{ij} ; z_{ij}), where x_j = Min (x_{ij}).y_j = $\left(\prod_1^n y_{ij}{}^{1/n}\right)$, and z_j=max(x_{ij}) (Mabrouk, 2021). The validation process involves evaluating the criteria by determining the approval weight and fuzzy scale (Jahanvand et al., 2023).

This study uses a triangular fuzzy spectrum for a five-point likert scale on the significance of criteria, as presented in **Table 3**.

The application of FDM is used to correct significant factors with a threshold using Equation (2). In the initial stage, 38 criteria in **Table 2** are analyzed in round 1 based on the expertise and assessment of experts. After review, evaluation results are obtained from FDM and TFNs, as shown in **Table 4**.

Based on the data in **Table 4**, it was found that there are variables that are eliminated because they did not reach the specified threshold. Therefore, experts conducted a second round of evaluation of the selected variables to produce a consensus value. Changes in the index of each variable are shown through the illustration in **Figure 3**. Furthermore, naming is built based on the evaluation results, as shown in **Table 5**.

Based on the evaluation results by experts using the Fuzzy Delphi method, the agreement is that 12 factors and 27 criteria are in consensus. All criteria are essential above the threshold for decision-making.

Table 4. Result of evaluation of criteria.

No.	Code	Criteria	DFM score	Decision
1.	A1	Skilled labor	0.563	Accepted
2.	A2	Natural disasters	0.600	Accepted
3.	A3	Technological infrastructure	0.575	Accepted
4.	B1	Growth trends	0.588	Accepted
5.	B2	Inflation rates	0.275	*Rejected*
6.	B3	Currency stability	0.563	Accepted
7.	C1	Regional environmental initiatives	0.600	Accepted
8.	C2	Policies	0.542	Accepted
9.	C3	Competitive landscape	0.600	Accepted
10.	D1	Local innovation ecosystems	0.600	Accepted
11.	D2	Digital infrastructure	0.675	Accepted
12.	E1	Demographic makeup	0.588	Accepted
13.	E2	Cultural heritage	0.625	Accepted
14.	E3	Diversity	0.625	Accepted
15.	F1	Community engagement	0.304	*Rejected*
16.	F2	Social inclusion	0.488	*Rejected*
17.	F3	Consumer behaviors	0.625	Accepted
18.	G1	Political environment	0.600	Accepted
19.	G2	Governance structures	0.638	Accepted
20.	H1	Crime rates	0.600	Accepted
21.	H2	Internal security	0.638	Accepted
22.	H3	Law enforcement	0.625	Accepted
23.	I1	Age distribution	0.663	Accepted
24.	I2	Population growth	0.171	*Rejected*
25.	I3	Urbanization	0.563	Accepted
26.	I4	Education levels	0.613	Accepted
27.	L5	Literacy rates.	0.250	*Rejected*
28.	J1	Rural distribution	0.625	Accepted
29.	J2	Land for development	0.613	Accepted
30.	K1	Climate	0.213	*Rejected*
31.	K2	Natural disaster	0.233	*Rejected*
32.	K3	Environmental risks	0.213	*Rejected*
33.	L1	Policing	0.600	Accepted
34.	L2	Emergency services	0.675	Accepted
35.	L3	Disaster preparedness	0.250	*Rejected*
36.	L4	Data protection	0.613	Accepted
37.	M1	Digital infrastructure	0.250	*Rejected*
38.	M2	Border control	0.288	*Rejected*

Table 5. Result of congruence for each criterion.

Initial code	Renamed	Variable (subcriteria)	Initial code	Renamed	Variable (subcriteria)
A1	J2	Land for Development	G1	H2	Internal security
A2	H3	Law enforcement	G2	B1	Growth trends
A3	J1	Rural distribution	H1	G1	Political environment
B1	I4	Education levels	H2	B3	Currency stability
B3	L1	Policing	H3	D1	Innovation ecosystems
C1	F3	Consumer behaviors	I1	A3	Technological
C2	L4	Data protection	I3	L2	Emergency services
C3	G2	Governance structures	I4	E2	Cultural heritage
D1	H1	Crime rates	J1	D2	Digital infrastructure
D2	A1	Skilled labor	J2	E3	Diversity
E1	I3	Urbanization	L1	I1	Age distribution
E2	C1	Regional environmental	L2	A2	Natural disasters
E3	C2	Policies	L4	E1	Demographic makeup
F3	C3	Competitive landscape			

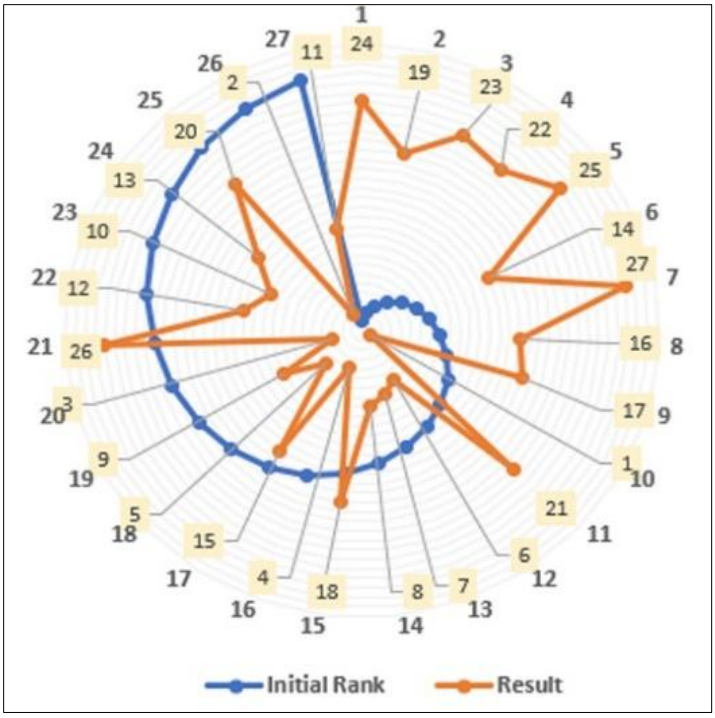

Figure 3. Result of evaluation of variable index based on the FDM.

3.2. Determination of Criteria Weight

The purpose of weighting criteria is to declare the level of each criterion according to the rank assessed based on priority level (Barik et al., 2024). Following applying the fuzzy Delphi method to evaluate the criteria, alterations were observed in the hierarchical positioning of several criteria. In the next stage, The weight of each criterion and instrument is calculated using the Rank Reciprocal (Faisal and Rahman, 2023a), in which the total of criteria is 27.

Based on the criteria collected, the weight value calculation is carried out using Equation (3), as known:

$n = 27$

$w_i : 1..27 = \frac{1}{1} \ldots \ldots \frac{1}{27}$

$w_i : 1..27 = 1.00 \ldots .. 0.0370$; $w_i : 1..27 = 1.00 + \ldots + 0.0370 = 3.8915$

$w_i : 1 = \frac{1}{3.8915} = 0.2570$

$w_i : 27 = \frac{0.0370}{3.8915} = 0.0095$

The result of determining the weighted criteria is shown in **Table 6**.

In **Table 6**, it can be seen that the determination of weight values is based on variable factors and criteria to adjust the relative importance of each criterion according to priority or preference.

Table 6. Result of congruence for each criterion.

No.	Code factor	Factor weight	Code criteria	Criteria	Criteria weight
1.	J	0.0314	J2	Land for development	0.2570
2.	H	0.0393	H3	Law enforcement	0.1285
3.	J	0.0314	J1	Rural distribution	0.0857
4.	I	0.0349	I4	Education levels	0.0642
5.	L	0.0262	L1	Policing	0.0514
6.	F	0.0524	F3	Consumer behaviors	0.0428
7.	L	0.0262	L4	Data protection	0.0367
8.	G	0.0449	G2	Governance structures	0.0321
9.	H	0.0393	H1	Crime rates	0.0286
10.	A	0.3145	A1	Skilled labor	0.0257
11.	I	0.0349	I3	Urbanization	0.0234
12.	C	0.1048	C1	Regional environmental initiatives	0.0214
13.	C	0.1048	C2	Policies	0.0198
14.	C	0.1048	C3	Competitive landscape	0.0184
15.	H	0.0393	H2	Internal security	0.0171
16.	B	0.1572	B1	Growth trends	0.0161
17.	G	0.0449	G1	Political environment	0.0151
18.	B	0.1572	B3	Currency stability	0.0143
19.	D	0.0786	D1	Local innovation ecosystems	0.0135
20.	A	0.3145	A3	Technological infrastructure	0.0128
21.	L	0.0262	L2	Emergency services	0.0122
22.	E	0.0629	E2	Cultural heritage	0.0117
23.	D	0.0786	D2	Digital infrastructure	0.0112
24.	E	0.0629	E3	Diversity	0.0107
25.	I	0.0349	I1	Age distribution	0.0103
26.	A	0.3145	A2	Natural disasters	0.0099
27.	E	0.0629	E1	Demographic makeup	0.0095

3.3 Integration MOO in MCGDM

Appropriate assessment, techniques, precise computations, and high-quality raw data are necessary for producing high-quality output or making decisions (Stević et al., 2022). This research uses the MOO-MCGDM approach to simultaneously address complex and dynamic problems through optimization. The analysis of the application of MOO-MCGDM is explained in the following way. Evaluation and determination of criteria weight are done using Fuzzy Delphi and Rank Reciprocal methods, and then the type of each criterion is determined, as presented in **Table 7**.

Assessment of regional expansion feasibility using existing criteria by the government or experts within each regency group. The test involved 5 districts and 25 subdistricts in the Luwu - Indonesia, Ai region (i = 1, 2, 3, 4, 5) to evaluate the feasibility of region expansion using 27 criteria. Next to the criteria in **Table 7**, their type is also given, where max indicates benefit type criteria, while min indicates cost type criteria. The Rank Reciprocal weight is used to evaluate the districts by criteria, as shown in **Table 8**.

Furthermore, an initial matrix is scored and formed on each regency, as shown in **Tables 9**, **10**, **11**, **12**, and **13**. In the assessment process, the criteria are set based on their type: max for the benefit criterion, where a higher value means profitable, and min for the cost criterion, where a lower value means profitable.

Based on scoring data and preliminary decision matrices in **Tables 9, 10, 11, 12,** and **13**, its elements are normalized. The normalization of the benefit type criteria consists of H3, F3, G2, H1, A1, C1, C2, C3, H2, B1, G1, B3, D1, A3, E2, D2, E3, A2, E1 are carried out using Equation (6) based on notation (x^-). In contrast, normalization of the cost criteria consisting of L2, I1, J2, J1, I4, L1, L4, and I3 using Equation (7) based on notation (x^+). **Table 14** shows examples of normalization results specific to Kec-1 in each regency. Next, calculate the value of the weighted matrix (V) using Equation (8) with the results shown in **Table 14**.

Table 7. Weight of the criteria.

No.	Code	Criteria	fw_j	Type
1.	J2	Land for development	0.008	Cost
2.	H3	Law enforcement	0.005	Benefit
3.	J1	Rural distribution	0.008	Cost
4.	I4	Education levels	0.002	Cost
5.	L1	Policing	0.001	Cost
6.	F3	Consumer behaviors	0.002	Benefit
7.	L4	Data protection	0.001	Cost
8.	G2	Governance structures	0.001	Benefit
9.	H1	Crime rates	0.005	Benefit
10.	A1	Skilled labor	0.008	Benefit
11.	I3	Urbanization	0.002	Cost
12.	C1	Regional environmental initiatives	0.002	Benefit
13.	C2	Policies	0.002	Benefit
14.	C3	Competitive landscape	0.002	Benefit
15.	H2	Internal security	0.005	Benefit
16.	B1	Growth trends	0.003	Benefit
17.	G1	Political environment	0.001	Benefit
18.	B3	Currency stability	0.002	Benefit
19.	D1	Local innovation ecosystems	0.001	Benefit
20.	A3	Technological infrastructure	0.008	Benefit
21.	L2	Emergency services	0.001	Cost
22.	E2	Cultural heritage	0.0007	Benefit
23.	D2	Digital infrastructure	0.0011	Benefit
24.	E3	Diversity	0.00074	Benefit
25.	I1	Age distribution	0.0022	Cost
26.	A2	Natural disasters	0.0081	Benefit
27.	E1	Demographic makeup	0.0007	Benefit

Table 8. Linguistic scale for evaluating the district.

Linguistic terms	Linguistic values
Very Good (1)	0.48
Good (2)	0.24
Fair (3)	0.16
Poor (4)	0.12

Table 9. Scoring criteria and initial matrix for each subdistrict in regency Luwu-A.

Subdistrict	Criteria																									
	J2	H3	J1	I4	L1	F3	L4	G2	H1	A1	I3	C1	C2	C3	H2	B1	G1	B3	D1	A3	L2	E2	D2	E3	I1	A2	E1
Kec I	3	4	3	2	4	3	2	2	3	2	3	3	3	4	4	3	4	4	3	3	4	2	2	2	3	2	2
Kec II	4	3	4	2	3	2	4	2	3	4	3	3	4	3	3	2	4	4	4	3	4	4	3	3	2	3	3
Kec III	4	4	4	2	3	2	2	4	2	4	3	2	3	3	2	3	2	4	4	3	2	3	4	4	3	2	2
Kec IV	3	4	3	2	3	4	2	4	2	2	4	4	4	3	4	2	3	3	4	2	4	2	3	3	3	4	2
Kec V	2	4	3	2	4	4	2	4	4	2	2	2	2	3	2	2	2	4	3	4	2	4	2	3	3	3	4

Table 10. Scoring criteria and initial matrix for each subdistrict in regency Luwu-B.

Subdistrict	Criteria																									
	J2	H3	J1	I4	L1	F3	L4	G2	H1	A1	I3	C1	C2	C3	H2	B1	G1	B3	D1	A3	L2	E2	D2	E3	I1	A2	E1
Kec I	4	3	4	3	4	4	3	3	3	4	4	3	4	3	3	4	3	3	4	3	3	3	4	4	4	4	4
Kec II	4	4	4	3	3	3	3	4	3	3	4	4	4	3	3	4	3	3	4	3	3	4	3	3	3	3	4
Kec III	3	3	3	3	4	4	3	4	4	4	3	3	4	4	4	3	4	4	3	4	4	4	4	4	4	4	3
Kec IV	4	4	4	4	3	3	4	3	3	4	4	3	3	4	4	3	3	4	4	3	4	4	3	4	3	4	4
Kec V	4	3	3	3	4	4	4	3	3	4	3	4	3	4	3	4	3	3	4	4	4	4	4	4	3	4	3

Table 11. Scoring criteria and initial matrix for each subdistrict in regency Luwu-C.

Subdistrict	Criteria																									
	J2	H3	J1	I4	L1	F3	L4	G2	H1	A1	I3	C1	C2	C3	H2	B1	G1	B3	D1	A3	L2	E2	D2	E3	I1	A2	E1
Kec I	3	4	4	3	1	4	4	4	3	3	4	4	4	4	4	3	3	3	4	4	3	3	4	4	3	3	3
Kec II	4	3	4	3	4	4	4	4	4	3	4	4	4	3	3	3	4	4	3	4	3	3	4	3	4	3	3
Kec III	4	2	3	4	3	4	4	2	3	2	3	4	3	3	2	4	3	3	3	4	4	4	3	3	3	3	3
Kec IV	4	3	4	4	4	4	2	4	3	3	3	3	3	3	3	3	4	3	4	3	3	3	3	3	4	4	4
Ke V	4	4	4	3	3	3	3	4	4	4	3	3	3	3	3	2	3	3	4	3	4	4	4	3	3	3	3

Table 12. Scoring criteria and initial matrix for each subdistrict in regency Luwu -D.

Subdistrict	Criteria																									
	J2	H3	J1	I4	L1	F3	L4	G2	H1	A1	I3	C1	C2	C3	H2	B1	G1	B3	D1	A3	L2	E2	D2	E3	I1	A2	E1
Kec I	1	2	2	4	2	3	2	4	1	1	2	1	2	2	2	3	2	2	4	4	3	2	2	2	3	4	2
Kec II	2	3	1	1	1	4	3	1	3	2	2	4	1	1	3	3	1	1	4	4	3	1	4	4	3	4	1
Kec III	4	1	3	2	2	2	3	2	2	2	2	3	4	1	2	2	2	1	1	2	1	4	4	1	4	1	4
Kec IV	2	4	1	1	4	4	2	4	1	2	1	1	4	2	2	3	3	4	2	4	2	3	3	1	3	1	3
Kec V	3	4	4	4	2	2	4	1	4	3	3	4	4	2	4	3	4	3	3	4	2	1	1	1	2	2	4

Table 13. Scoring criteria and initial matrix for each subdistrict in regency Luwu-E.

Subdistrict	Criteria																									
	J2	H3	J1	I4	L1	F3	L4	G2	H1	A1	I3	C1	C2	C3	H2	B1	G1	B3	D1	A3	L2	E2	D2	E3	I1	A2	E1
Kec I	4	1	3	3	2	2	2	1	1	4	1	1	3	1	3	3	4	3	2	3	1	3	4	3	4	1	2
Kec II	3	3	1	2	3	1	1	1	1	1	3	3	4	2	4	3	3	4	3	4	4	2	4	1	1	3	3
Kec III	1	4	1	2	4	1	3	1	4	1	1	1	2	4	3	1	3	3	2	4	4	2	3	3	2	3	4
Kec IV	3	3	3	2	1	4	3	1	1	3	1	1	4	4	2	4	4	4	4	2	2	1	3	1	2	2	2
Kec V	3	4	2	1	1	2	1	3	1	1	1	3	2	1	2	3	1	4	2	2	2	3	3	3	3	2	4

Table 14. Result of normalization of initial decision matrix.

Regency - Subdistrict	J2	H3	J1	I4	L1	F3	L4	G2	H1	..	E1
Luwu A : Kec I	0.5	1	1	1	0	0.5	1	0	0.5	..	0
Luwu B : Kec I	0	0	0	1	0	1	1	0	0	..	1
Luwu C : Kec I	1	1	0	1	1	1	0	1	0	..	0
Luwu D : Kec I	1	0.33	0.66	0	0.66	0.5	1	1	0	..	0.33
Luwu E : Kec I	0	0	0	0.5	0.66	0.33	0.5	0	0	..	0

Calculating the elements of the weighted matrix was performed by multiplying the weight coefficients of the factor in **Table 6** and criteria in **Table 7** with elements of the normalized matrix in **Table 14**.

An example of the calculation is given in the LUWU-A: Kec 1 (V11) for criteria J2 as follows:

fw_1 = f1 * w1 = 0.0314 * 0.257 = 0.0081.

V11 = (fw1 * t11) + fw1 = (0.0081 * 0.5) + 0.0081 = 0.012.

where, t11 is an element of the normalized matrix (N), and fw1 is the weight coefficient of factor and criterion, as presented in **Table 15**.

Table 15. Result of elements of the weighted matrix (V).

Regency - Subdistrict	J2	H3	J1	I4	L1	F3	L4	G2	H1	..	E1
Luwu A : Kec I	0.012	0.010	0.016	0.004	0.001	0.003	0.003	0.001	0.008	..	0.001
Luwu B : Kec I	0.008	0.005	0.008	0.004	0.001	0.004	0.003	0.001	0.005	..	0.001
Luwu C : Kec I	0.016	0.010	0.008	0.004	0.003	0.004	0.001	0.003	0.005	..	0.001
Luwu D : Kec I	0.016	0.007	0.013	0.002	0.002	0.003	0.003	0.003	0.005	..	0.001
Luwu E : Kec I	0.008	0.005	0.008	0.003	0.002	0.003	0.002	0.001	0.005	..	0.001

At the stage of determining the matrix of the estimated limit area (G), calculations are carried out using Equation (9), where the value of m (alternative) = 5 is known, so set m = 1/5 = 0.2. Data for criterion J2 in **Table 16** is obtained as follows:

g1 = $\left(\prod_{j=1}^{5} v_{ij}\right)^{1/5}$ = (0.012 * 0.008 * 0.008 * 0.012 * 0.016)0.2. = 0.011.

The results of calculating the matrix of the estimated area of limitation (G) by each subdistrict in The LUWU-A are shown in **Tables 16** and **17**.

Table 16. Matrix of approximate area of limitation (G) the criterion between 1 to 14.

G	J2	H3	J1	I4	L1	F3	L4	G2	H1	A1	I3	C1	C2	C3
	0.011	0.009	0.012	0.003	0.002	0.003	0.002	0.002	0.007	0.011	0.003	0.003	0.003	0.003

Table 17. Matrix of approximate area of limitation (G) the criterion between 15 to 27.

G	H2	B1	G1	B3	D1	A3	L2	E2	D2	E3	I1	A2	E1
	0.007	0.003	0.002	0.004	0.002	0.012	0.002	0.001	0.001	0.001	0.003	0.011	0.001

The difference between the weighted matrix (V) elements and the values from the border approximation area matrix (G) is used to calculate the regency's distance. Equation (10) is used to extract the element q11 from the matrix of the alternative's distance from the border approximation region (Q). Given an example for determining the value of LUWU A-1 criterion J2 as follows:

Q11\ = v11 – g1 = 0.012 – 0.011 = 0.001.

Examples of calculation results obtained in each regency group are shown in **Table 18**.

Table 18. Matrix element of alternate distance - approximate border area.

Regency	J2	H3	J1	I4	L1	F3	L4	G2	H1	..	E1
Luwu A-1	*0.001*	0.001	0.004	0.001	-0.001	0.000	0.000	-0.001	0.001	..	0.000
Luwu B-1	-0.001	-0.002	-0.003	0.002	0.000	0.001	0.001	0.000	-0.001	..	0.000
Luwu C-1	0.007	0.002	-0.001	0.002	0.001	0.001	0.000	0.000	-0.002	..	0.000
Luwu D-1	0.004	-0.001	0.001	0.000	0.000	0.000	0.001	0.001	-0.002	..	0.000
Luwu E-1	-0.003	-0.003	-0.003	0.000	0.000	0.000	0.000	0.000	-0.001	..	0.000

Based on the alternate distance (Q) value in **Table 18**, each regency group is calculated using Equation (11). Given the example calculation of the criterion function of the subdistrict-1 in the Luwu-D as follows: S1 = $\sum_{j=1}^{10} q_{1j}$ = 0.004 + (-0.001) + 0.001 + 0.001 + 0.001 + (-0.002) + (-0.004) + (-0.001) + (-0.001) + 0.001 + (-0.001) + 0.001 + 0.002 + 0.005 = 0.0052. The results of each regency are shown in **Table 19**.

Table 19. Result of MABAC calculation for each regency group.

Regency		Luwu A	Luwu B	Luwu C	Luwu D	Luwu E
Subdistrict	1	0.0081	-0.0045	0.0207	*0.0052*	-0.0079
	2	-0.0011	-0.0139	0.0068	0.0149	0.0157
	3	-0.0031	0.0347	-0.0001	-0.0216	0.0184
	4	0.0086	0.0016	-0.0009	0.0123	0.0016
	5	0.0138	0.0134	-0.0006	0.0122	-0.0031

After obtaining scores for each regency group, the next stage is to determine the feasibility value of overall regional development using the BORDA method. Based on the data in **Table 19**, an encoding process was

carried out on the subdistrict score > 0 is stated as 1, while the subdistrict score ≤ 0 is stated to be 0. Given the example calculation of the BORDA function for the regency of Luwu-D using Equation (18):

$$B_i = \sum_i ES_i * w_j \quad (18)$$

where,

B_i = BORDA Score; ESi = Encode ($\frac{0}{1}$) for regency value

w_j = Weight of rank based on Rank Reciprocal.

B_i = (1 * 0.4379) + (1 * 0.2189) + (0 * 0.1459) + (1 * 0.1094) + (1 * 0.875) = 0.854.

The calculation results of the BORDA method are shown in **Table 20**.

Based on the calculations outlined in **Table 20**, the suitability value assigned to the Luwu-D regency group is quantified at 0.854, which has been identified as the optimal value for determining regional suitability.

Sensitivity tests can help identify the variables that affect the final result the most, so that focus can be made on the most important variables and ensure that the information related to those variables is accurate and reliable. Therefore, a sensitivity test was carried out on factors indicated to significantly influence the results, which was carried out by adding a value of 0.5 to the weight of the factor. **Tables 21**, **22**, and **23** show the sensitivity test results.

Table 20. Result of encoded value for each regency group.

Regency	Subdistrict					Score	Rank
	I	II	III	IV	V		
LUWU A	1	0	0	1	1	0.635	3
LUWU B	0	0	1	1	1	0.343	5
LUWU C	1	1	0	0	0	0.657	2
LUWU D	1	1	0	1	1	*0.854*	*1*
LUWU E	0	1	1	1	0	0.474	4
Weight of rank	0.4379	0.2189	0.1459	0.1094	0.0875		

Table 21. Result of sensitivity test factor A to D.

REGION	Factor A						Factor B						Factor C						Factor D					
	Subdistrict					Rank	Subdistrict					Rank	Subdistrict					Rank	Subdistrict					Rank
	I	II	III	IV	V		I	II	III	IV	V		I	II	III	IV	V		I	II	III	IV	V	
LUWU A	1	0	0	1	1	3	1	0	1	1	1	3	1	1	0	1	1	1	1	1	1	1	1	1
LUWU B	0	0	1	0	1	5	0	0	1	1	1	5	0	0	1	0	1	5	1	0	1	0	1	4
LUWU C	1	1	0	0	0	2	1	1	1	0	0	2	1	1	1	0	0	3	1	1	0	0	1	3
LUWU D	1	1	0	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	0	1	1	2
LUWU E	0	1	1	1	0	4	0	1	1	1	1	4	0	1	1	1	0	4	0	1	1	1	0	5

Table 22. Result of sensitivity test factor E to H.

REGION	Factor E						Factor F						Factor G						Factor H					
	Subdistrict					Rank	Subdistrict					Rank	Subdistrict					Rank	Subdistrict					Rank
	I	II	III	IV	V		I	II	III	IV	V		I	II	III	IV	V		I	II	III	IV	V	
LUWU A	1	1	0	1	1	2	1	0	0	1	1	4	1	0	0	1	1	3	1	0	0	1	1	2
LUWU B	0	0	1	1	1	5	1	0	1	0	1	3	0	0	1	0	1	5	0	0	1	1	0	5
LUWU C	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	0	2	1	1	0	0	1	1
LUWU D	1	1	0	1	1	2	1	1	0	1	1	2	1	1	0	1	1	1	0	1	0	1	1	3
LUWU E	0	1	1	0	1	4	0	1	1	1	0	5	0	1	1	1	1	4	0	1	1	0	0	4

Table 23. Result of sensitivity test factor I to L.

REGION	Factor I						Factor J						Factor L					
	Subdistrict					Rank	Subdistrict					Rank	Subdistrict					Rank
	I	II	III	IV	V		I	II	III	IV	V		I	II	III	IV	V	
LUWU A	1	1	0	1	1	1	1	0	0	1	1	2	0	0	1	1	1	5
LUWU B	0	0	1	0	1	5	0	0	1	0	1	5	1	1	1	0	0	3
LUWU C	1	0	1	0	1	3	1	0	1	0	0	3	1	1	0	1	0	4
LUWU D	1	1	0	1	1	1	1	1	0	1	0	1	1	1	0	1	1	1
LUWU E	0	0	1	1	0	4	0	1	1	0	1	4	1	1	0	1	1	1

Based on the results of sensitivity tests in **Tables 21**, **22**, and **23**, it is known that the hybrid MABAC - BORDA methods show high sensitivity to weight changes in factors C, D, E, F, H, I, J, and L. In contrast, factors A, B, and G remain stable to weight changes. This indicates that the decision-makers required in-depth analysis and accurate data. Therefore, as support for the results of the MCGDM process, a sentiment analysis process is carried out to reduce bias and subjectivity from the weight of certain variables.

3.4 Sentiment Analyst

This study conducted a trial involving 900 respondents to provide comments through questionnaire techniques, of which 70% are used as training data and 30% as test data. Using sentiment analysis on 900 citizen comments provides valuable insights into public opinion, which is important for regional expansion decision-making. Citizen sentiment can highlight potential community attention or support, which must be taken into account in the planning process to ensure that local policies are aligned with the needs and expectations of the community. Citizen sentiment is divided into negative, neutral, and positive classes to group and analyze texts based on the nuances of sentiment, as shown in **Table 24**.

Table 24. The comments of communities regarding the discourse on regional expansion.

No.	Comments
L1	Pemekaran wilayah Provinsi Luwu perlu dipertimbangkan dampak secara matang untuk menghindari masalah baru. (*The expansion of the Luwu Province area needs to be carefully considered to avoid new problems*)
L2	Pemekaran wilayah di Provinsi Luwu dinilai akan mempercepat pembangunan dan pelayanan publik. (*The expansion of areas in Luwu Province is considered to accelerate development and public services*)
L3	Pemekaran wilayah Provinsi Luwu menuai pro dan kontra di kalangan warga. (*The expansion of Luwu Province reaps pros and cons among residents*)
…	…
L899	Diharapkan dengan pemekaran wilayah distribusi anggaran di Provinsi Luwu lebih merata. (*It is expected that with the expansion of the budget distribution area in Luwu Province, it will be more evenly distributed*)
L900	Adanya pemekaran wilayah membuka diskusi tentang cara terbaik untuk mengatur administrasi dan pemerintahan yang lebih efektif. (*The expansion of territories opened discussions about how best to organize administration and government more effectively*)

After carrying out several stages in text pre-processing, namely case folding, tokenizing, filtering, and stemming. Testing and analysis using training data are conducted to determine the accuracy of applying the Naïve Bayes method to determining a sentiment class. Testing done on a comment "*Perlu ada transparansi dalam proses pemekaran wilayah agar masyarakat dapat terlibat secara aktif*" (There needs to be transparency in the process of regional expansion so that the community can be actively involved). The results of pre-processing text can be seen in **Table 25**.

Table 25. Preprocessing-text community comments.

Pre-processing-text	Result	Sentiment
Comment (U1)	perlu ada transparansi dalam proses pemekaran wilayah agar masyarakat dapat terlibat secara aktif	???
Tokenizing	[‘perlu’, ’ada’, ‘transparansi’, ’dalam’, ‘proses’, ‘pemekaran’, ‘wilayah’, ‘agar’, ‘masyarakat’, ‘dapat’, ‘terlibat’, ‘secara’, ‘aktif’]	
Stopword	perlu, transparansi, proses, pemekaran, wilayah, masyarakat, terlibat, aktif	
Stemming	perlu, transparansi, proses, mekar, wilayah, masyarakat, terlibat, aktif	

Table 26. Test data vectorization on neutral sentiment class.

Word	N_i	N	Vocabulary
perlu	141	1003	3348
transparansi	112		
proses	0		
pemekaran	29		
wilayah	16		
masyarakat	0		
terlibat	16		
aktif	16		

The test data that has gone through the pre-processing text stage is then vectorized or calculated as the weight of each word in each sentiment class (Jufri et al., 2024). **Table 26** shows the results of calculating the weight of each word in the Neutral sentiment class.

Based on the data in **Table 26**, the analysis of the test data classification process was carried out as follows:

Step 1: Calculate the probability of each sentiment class using Equation (14).

$$P(\text{class\_sentiment}) = \frac{\text{numer of class in test\_data}}{\text{number of test\_data}}$$

$$P(\text{Neutral}) = \frac{177}{400} = 0.442,\ P(\text{Positive}) = \frac{102}{400} = 0.255,\ P(\text{Negative}) = \frac{121}{400} = 0.302$$

Step 2: Calculate the probability of each word involving the weighted value of the word in the Neutral sentiment class by applying Equation (15).

$$P(\text{word} = \text{perlu} \mid \text{sentiment} = \text{Neutral}) = \frac{141 + 1}{11003 + 3348} = 0.033$$

$$P(\text{word} = \text{transparansi} \mid \text{sentiment} = \text{Neutral}) = \frac{121 + 1}{11003 + 3348} = 0.026$$

$$P(\text{word} = \text{proses} \mid \text{sentiment} = \text{Neutral}) = \frac{0 + 1}{11003 + 3348} = 0.0002$$

$$P(\text{word} = \text{pemekaran} \mid \text{sentiment} = \text{Neutral}) = \frac{29 + 1}{11003 + 3348} = 0.007$$

$$P(\text{word} = \text{wilayah} \mid \text{sentiment} = \text{Neutral}) = \frac{16 + 1}{11003 + 3348} = 0.004$$

Likelihood (Neutral) = 0.033 * 0.026 * 0.0002 * 0.007 * 0.004 * 0.0002 * 0.004 * 0.004 = 1.53754E-20.

Step 3: Calculate the maximum value by multiplying the probability value of each sentiment class using Equation (13).

V(Neutral) = 0.442 * 1.53754E-20 = 6.79593E-21.

V(Negative) = 0.255 * 1.92E-21 = 4.896E-22.

V(Positive) = 0.302 * 2.37E-28 = 7.1574E-29.

Vmap = argmax (V(Neutral) | V(Negative) | V(Positive)).

Vmap = argmax (6.79593E-21) | (4.896E-22) | (7.1574E-29).

The most significant probability value (6.79593E-21) test data (U1) is determined to be found in the neutral sentiment class. The results of the evaluation of the entire test data using orange software are shown in **Table 27**, which shows the classification accuration value is 0.979 and precision is 0.971.

Table 27. Results of the evaluation of the entire test data.

Model	AUC	CA	F1	Precision	Recall
Random forest	0.978	0.97	0.97	0.971	0.97
Neural network	0.978	0.97	0.97	0.971	0.97
Naive Bayes	0.979	0.97	0.97	0.971	0.97

Furthermore, it is known that the comments test data included in the class sentiment group neutral (44%), negative (30%), and positive (26%).

3.5 Implementation of Fuzzy-KNN

Fuzzy KNN has been widely used in various classification and regression tasks (Wu et al., 2021) and is useful in making machine learning-based strategic decisions (Jumarlis et al., 2024). The FKNN classification method in this study predicts test data using the value of membership degrees in each class to ensure the classification results. Applying the FKNN method involves several criteria from CBS of Indonesia and the results of the MCGDM calculation (MGS), and sentiment class of regions including Sentiment Class Score (SCS), Global Food Security Index (GFSI), Human Development Index (HDI), Happiness Index (HI), Water Quality Index (WQI), Poverty Gap Index (PGI), Consumer Price Index (CPI), Regional Competitiveness Index (RCI), as presented in **Table 28**.

Table 28. Sample of dataset region expansion.

Data	Regions	Internal source		External source							Result
		MGS	SCS	GFSI	HDI	HI	WQI	PGI	CPI	RCI	
D1	Aceh Barat	0.73	1	77.98	71.38	75.5	61.50	17.93	104.74	2.69	Pending
D2	Banten	0.75	1	76.07	72.45	72.61	58.93	12.51	104.18	3.62	Autonomous
D3	Flores	0.80	0	72.36	64.22	74.61	54.65	10.20	103.00	2.74	Pending
D4	Gorontalo	0.80	1	79.25	68.68	78.63	58.70	17.10	106.51	3.15	Autonomous
D5	Halmahera Raya	0.84	1	73.39	67.50	80.88	55.87	8.43	105.36	2.65	Pending
D6	Jambi Barat	0.71	0	79.73	69.01	76.70	61.20	8.33	106.37	2.99	Pending
D7	Kaltara	0.80	1	82.02	75.83	79.75	54.46	6.30	106.11	3.19	Autonomous
D8	Kapuas Raya	0.78	0	72.41	65.69	76.20	56.69	8.59	105.09	2.57	Pending
D9	Bangka Belitung	0.79	1	84.59	71.47	76.44	57.63	4.45	105.55	3.04	Autonomous
D10	Kepulauan Nias	0.81	1	65.29	61.93	73.60	53.50	16.48	105.14	2.31	Pending
D11	Kepulauan Riau	0.89	1	63.26	72.71	75.58	56.79	6.78	106.72	3.16	Autonomous
D12	Madura	0.79	0	63.29	62.93	74.61	56.13	6.50	105.88	2.70	Pending
D13	Maluku Utara	0.82	1	73.39	71.25	80.88	55.69	6.23	105.53	3.66	Autonomous
D14	Papua Barat	0.79	1	71.89	71.67	78.27	62.00	21.33	104.34	2.92	Autonomous
D15	Sulawesi Barat	0.86	0	77.83	68.15	76.84	56.41	5.09	103.72	3.10	Autonomous
D16	*Luwu Raya*	0.85	0	77.23	70.51	76.42	57.79	6.81	105.36	2.82	?????

Based on input data on each criterion, the stages of FKNN calculation are carried out as follows:

Step 1: Specifies the value of *"k"* (the number of nearest neighbours where $1 \leq k \leq n$) and the value of n (the amount of training data).

Step 2: Calculate the membership value of the training data using a traditional two-condition classifier, in which the input pattern is set to *"x" ∈ "X"* can be a member or not be a member of a particular class, defined with the following characteristic function:

$$\mu Cc\ (x) = \begin{cases} 1\ if\ and\ only\ if\ x \in C_c \\ 0\ if\ and\ only\ if\ x \notin C_c \end{cases}.$$

Step 3: Calculate the euclidean distance of training data to the test data, then sort by ascending (Thamrin and Darniati, 2023) as presented in **Table 29**.

Table 29. Results of training membership data.

Data	D10	D12	D3	D11	D8	D15	D5	D2	D13	D14	D1	D6	D4	D9	D7
Sort ascending	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15
Euclidean distance	342.97	343.76	348.43	348.83	349.14	351.70	352.23	352.27	353.69	354.31	355.42	356.09	356.33	357.32	358.74

It is written in the example calculation training data (D1) against test data (D16) as follows:

$$D1 = \sqrt{\begin{matrix}(0.854 + 0.73)^2 + (0 + 1)^2 + (77.23 + 77.9)^2 + (70.51 + 71.38)^2 + (76.42 + 75.5)^2 \\ + (57.79 + 61.5)^2 + (6.81 + 17.93)^2 + (105.36 + 104.74)^2 + (2.82 + 2.69)^2 = 355.42\end{matrix}}$$

Step 4: Determine *"K"* nearest neighbours and refer to it as new data, where in the testing process, the value of *"k"* consists of 3, 7, 11, and 13. The result is presented in **Table 30**.

Table 30. The result of calculating Euclidean distance at each K-Value.

No.	**Training data ; Testing data**	**Euclide distance**	**K-Value**			
1.	D10;D16	342.97	3 Pending	7 Pending	11 Pending	13 Pending
2.	D12;D16	343.76				
3.	D3;D16	348.43				
4.	D11;D16	348.83				
5.	D8;D16	349.14				
6.	D15;D16	351.70				
7.	D5;D16	352.23				
8.	D12;D16	352.27				
9.	D13;D16	353.69				
10.	D14;D16	354.31				
11.	D1;D16	355.42				
12.	D6;D16	356.09				
13.	D4;D16	356.33				

Step 5: Calculate the membership value for the new data from each class using Equation (16). An example calculation is given at the value K = 7, where the set of euclidean distance member values consists of Pending Class (*CPend*) = {D10(342.97); D3(348.43); D8(349.14); D15(351.70)}, while Autonomous Class (*CAuto*) = {D12(343.76); D11(348.83); D5(352.23).

Next, with m = 2, the characteristic function assigns a weight of 1 to class members and 0 to non-members. The calculation process is described as follows:

$$CPend = \frac{\frac{1}{342.97^2}+\frac{1}{343.76^2}+\frac{1}{349.14^2}+\frac{1}{351.70^2}+\frac{0}{343.76^2}+\frac{0}{348.83^2}+\frac{0}{352.23^2}}{\frac{1}{342.97^2}+\frac{1}{343.76^2}+\frac{1}{349.14^2}+\frac{1}{351.70^2}+\frac{1}{343.76^2}+\frac{1}{348.83^2}+\frac{1}{352.23^2}} = \frac{3.30265E{-}05}{5.7767E{-}05} = 0.571.$$

$$CAuto = \frac{\frac{1}{343.76^2}+\frac{1}{348.83^2}+\frac{1}{352.23^2}+\frac{0}{342.97^2}+\frac{0}{343.76^2}+\frac{0}{349.14^2}+\frac{0}{351.70^2}}{\frac{1}{342.97^2}+\frac{1}{343.76^2}+\frac{1}{349.14^2}+\frac{1}{351.70^2}+\frac{1}{343.76^2}+\frac{1}{348.83^2}+\frac{1}{352.23^2}} = \frac{2.47405E\text{-}05}{5.7767E\text{-}05} = 0.428.$$

Finally, select the class with the most significant membership value using Equation (17), where the results show that the most significant value of 0.571 is in Class Pending, so it is stated that the test data of the Luwu Raya region is predicted to be in the Pending class. The test results are illustrated in **Figure 4**.

Further testing was done in the classification process based on KNN, FKNN, and Naïve Bayes using training data percentages of 50%, 75%, and 80%. The results of the evaluation with actual data are carried out using the confusion matrix method in Equations (19), (20), (21), and (22) as follows:

$$\text{Precision} = \frac{TP}{(TP + FP)} \quad (19)$$

$$\text{Recall} = \frac{TP}{(TP + FN)} \quad (20)$$

$$\text{F1 Score} = \frac{2(\text{Precision x Recall})}{(\text{Precision} + \text{Recall})} \quad (21)$$

$$\text{Accurate} = \frac{TP}{(TP+FP+FN)} \quad (22)$$

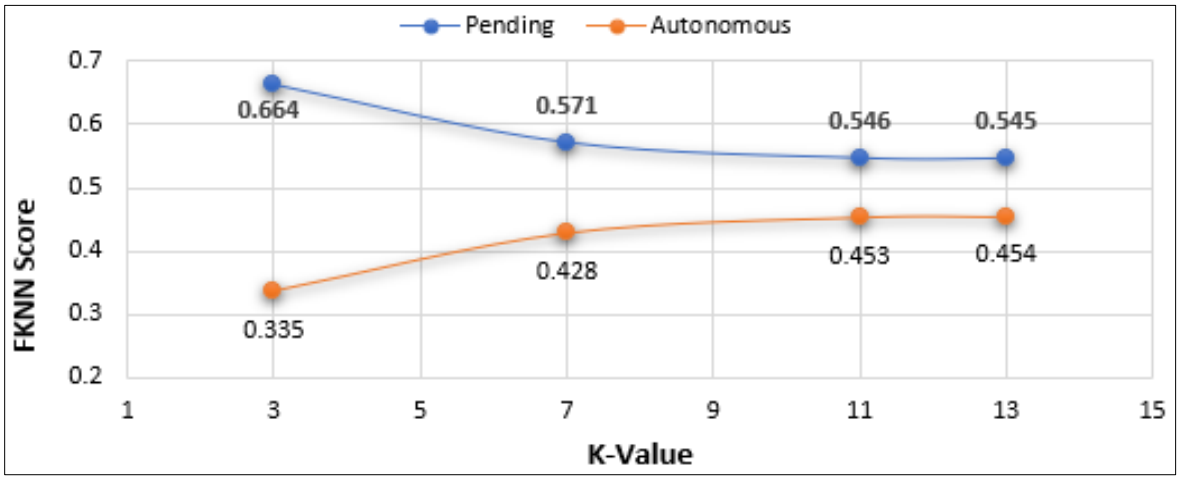

Figure 4. Result of FKNN calculation based on K-Value.

The evaluation results in **Figure 5** explain that KNN, FKNN, and Naive Bayes models show an increase in accuracy as the proportion of training data increases. FKNN consistently has higher accuracy than KNN and Naive Bayes. Based on Precision, Recall, and F1-Score, similar trends are observed with these metrics, where FKNN outperforms KNN and Naive Bayes across all training data proportions. The FKNN model achieves the highest 0.98 accuracy with 80% training data. This analysis indicates that the FKNN model performs better than the KNN and Naive Bayes model under all training data conditions, with higher accuracy, precision, recall, and F1-Score. The performance of models improves with more training data, demonstrating the importance of adequate data for model training.

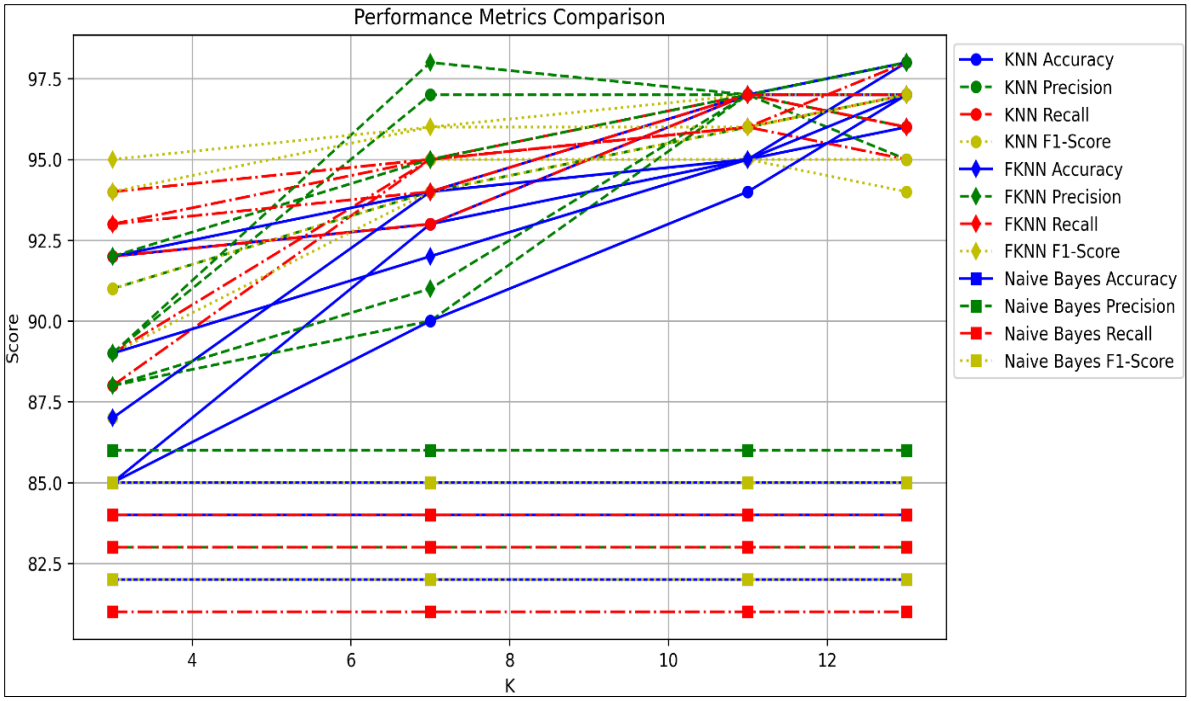

Figure 5. Result of confusion matrix evaluation based on FKNN - KNN - Naïve Bayes.

The limitation identified in this study is that implementing machine learning model frameworks relies heavily on the availability of relevant and high-quality data. However, collecting accurate, up-to-date, and comprehensive data is still difficult in underdeveloped areas. The framework reports an impressive accuracy score of 0.98, which shows high reliability and proves that it complies with the region of LUWU-Indonesia in 2024. Moreover, there could be potential biases or limitations within the dataset that should be carefully considered, likely using data exclusively from the Central Bureau of Statistics of Indonesia and analyzing only 900 citizen comments, which might not capture the full diversity of opinions and regional variations. It is essential to validate the model across different datasets and conduct sensitivity analyses to ensure its robustness.

4. Conclusions

The conclusions of this study validate and advance this field by proposing a comprehensive framework that integrates the MOO, MCGDM and sentiment analysis in machine learning to optimize regional expansion strategies. The proven efficacy of this framework highlights its potential to transform decision-making processes by systematically addressing and balancing conflicting objectives. Combining sentiment analysis with MOO and MCGDM, the study presents a holistic tool capable of effectively managing quantitative data and qualitative public sentiment, an increasingly important factor in contemporary regional planning.

Key contributions from this research include innovative adaptations of machine learning techniques to improve optimization algorithms and successful integration of group decision-making tools that incorporate diverse stakeholder perspectives, thus achieving an extraordinary accuracy score of 0.98. These findings demonstrate the practical usefulness of the proposed framework and open up new avenues for research in decision-making methodologies, especially concerning the growing interaction between technology, strategic frameworks, and stakeholder engagement.

In the future, the proposed framework has great potential for wider application, especially in areas such as urban planning and environmental management, in which complex and multi-purpose decision-making scenarios are prevalent. Further validation through real-world implementation, supported by continuous data updates and input from stakeholders, will be critical to improving the adaptability of these frameworks to diverse regional contexts. In addition, refinements of machine learning models in this framework can further improve prediction accuracy, thus enabling a more effective response to dynamic and evolving regional conditions. Therefore, this study lays a solid foundation for future research and practical application, making valuable contributions to the field of decision science, regional planning, and beyond.

Conflict of Interest

We declare that there is no conflict of interest regarding the study given in this paper. The study is carried out with full transparency and integrity, without influence or bias from the outside that can threaten the validity and objectivity of the results presented. The authors do not receive funding or other support from organizations or entities that may have an interest in the conclusions of this study.

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