Jurnal Sistem Komputer dan Informatika (JSON) Hal: 1593-1603
Volume 7, Nomor 4, Juni 2026
e-ISSN 2685-998X
DOI 10.30865/json.v7i4.9785

District Level Child Nutrition Vulnerability in North Sumatra Using Composite Indeks, Machine Learning Benchmarking

Fanny Ramadhani[1*], Sri Dewi[1], Dian Septiana[1], Diah Retno Wahyuningrum[2], Andy Satria[3]
[1] Faculty of Mathematics and Natural Science, Medan State University, Medan, Indonesia
[2] Faculty of Engineering, Medan State University, Medan, Indonesia
[3]Faculty of Engineering and Computer Science, Universitas Dharmawangsa, Medan, Indonesia
Email: [1*]fannyr@unimed.ac.id, [2] Sridewi@unimed.ac.id, [3] Dianseptiana.@unimed.ac.id, [4] diahretno@unimed.ac.id, [5]andysatria@dharmawangsa.ac.id
Correspondence Author Email: fannyr@unimed.ac.id[*]
Submitted: **09/05/2026**; Accepted: **27/06/2026**; Published: **30/06/2026**

Abstract- Child nutrition vulnerability is a multidimensional issue influenced by health outcomes, socioeconomic conditions, environmental factors, maternal education, dietary patterns, and access to health services. This study developed the Child Nutrition Vulnerability Index (IKGA) to map district level vulnerability in 33 districts or cities of North Sumatra during 2021-2023 and to examine the stability of the resulting priority ranking. Birth, severe malnutrition, and low birth weight data were obtained from the North Sumatra Provincial Health Office; sanitation was derived from Riskesdas; and supporting socioeconomic and service access variables were compiled from district level research and statistical datasets. The method included indicator transformation, annual min-max normalization, weighted composite aggregation, tertile-based relative risk classification, spatial visualization, one-at-a-time and Monte Carlo sensitivity analyses, and exploratory machine learning benchmarking using Random Forest, Decision Tree, and K-Means. The 2023 average IKGA was 0.3486, with the highest score in Nias (0.5573) and the lowest in Kota Binjai (0.1934). Monte Carlo sensitivity analysis produced an average Spearman rank correlation of 0.9957, indicating stable rankings under moderate weight variation. Random Forest reproduced the IKGA categories better than Decision Tree and K-Means, with 0.727 accuracy and 0.724 macro-F1. The IKGA provides an interpretable district level prioritization tool for SI-GIZI SIGAP, but the categories should be interpreted as relative provincial priorities rather than absolute nutritional risk thresholds.
Keywords: Child Nutrition; Composite Index; Risk Mapping; Sensitivity Analysis; Machine Learning Benchmarking

1. INTRODUCTION

Child undernutrition is a strategic public health problem, impacting growth, cognitive development, morbidity and long term human capital. Nutritional problems of children are commonly described as: stunting, wasting and underweight, severe malnutrition and low birth weight. But nutritional vulnerability is not a function of biological conditions alone. It is affected by household income, parental employment, maternal education, sanitation, availability of clean water, dietary practices, access to health services and spatial characteristics of districts or communities [1][2][3][4][5].

Indonesia has made great strides to reduce child undernutrition, but determinants vary by region. Previous studies have described that stunting in childhood in Indonesia is associated with poverty, maternal education, water, sanitation and hygiene conditions, and access to health services [6]. Spatial studies also suggest that undernutrition is geographically clustered, suggesting that intervention at the district level needs to be informed by local patterns of vulnerability rather than a uniform provincial program [7][8][9][10][11]. Therefore, a district level vulnerability instrument is needed to consolidate multiple indicators into an interpretable decision support measure.

The target population of the proposed index is children at the district or city level, while the unit of analysis is the district or city administrative area. In this study, severe malnutrition and LBW are treated as health-outcome indicators, whereas family income, unemployment, electricity access, sanitation, clean water availability, dietary pattern, maternal education, and health service access are treated as vulnerability factors. Thus, IKGA does not replace official nutritional status indicators; instead, it integrates multiple determinants into a district level score that can support priority setting.

North Sumatra is a region with diverse geographical and socio economic conditions. In island areas, coastal zones, and urban centers, districts have varying levels of access to services and household resources [10], [11]. A single nutrition indicator for monitoring might miss out on districts having a combination of moderate health burden and high environmental or socioeconomic risk. To overcome this limitation, a composite index can be constructed by combining several indicators with different units into a single comparable score [12][13][14].

Several machine learning approaches have been addressed for health-risk classification, such as decision trees, ensemble models, and clustering[15][16][17]. These methods can identify complex patterns in multidimensional data. Nevertheless, machine learning results are often less transparent than a composite index for policy communication. Thus, comparing a composite index with machine learning classifiers is useful for understanding whether the index based categories can be reproduced by data driven models. Therefore, machine learning in this

Jurnal Sistem Komputer dan Informatika (JSON)
Volume 7, Nomor 4, Juni 2026
e-ISSN 2685-998X
DOI 10.30865/json.v7i4.9785

study is positioned as exploratory benchmarking to examine whether the IKGA based categories can be reproduced from the same indicator set, not as an independent validation of the index.

Previous studies on child undernutrition in Indonesia have commonly examined individual determinants, household factors, spatial patterns, or machine learning classification separately. Limited studies have integrated district level health outcomes, socioeconomic conditions, environmental indicators, maternal education, service access, sensitivity testing, and model benchmarking into a single reproducible vulnerability mapping framework. The novelty of this study lies in the development of IKGA as an interpretable district level composite index and its use as an analytic foundation for SI-GIZI SIGAP, a web based decision support system intended for health offices, local stakeholders, administrators, and parents. The system is designed to provide vulnerability mapping, regional priority ranking, child growth monitoring, and evidence based intervention support.

This study aims to develop IKGA, analyze relative vulnerability trends from 2021 to 2023, map the 2023 risk distribution, evaluate weight sensitivity, prepare an expert validation framework, and benchmark the index based categories with Random Forest, Decision Tree, and K-Means. The expected contribution is a transparent analytic workflow for district level vulnerability mapping that can support data driven child nutrition decision making in North Sumatra.

2. RESEARCH METHODOLOGY

2.1 Research Stages

The research was conducted using a quantitative descriptive approach with composite-index development and model comparison. The unit of analysis was 33 districts or cities in North Sumatra Province, and the observation period covered 2021, 2022, and 2023. The main stages consisted of data collection, preprocessing, indicator transformation, normalization, weighted aggregation, risk classification, trend analysis, spatial visualization, sensitivity testing, expert validation framework preparation, and machine learning comparison. Figure 1 summarizes the stages of the analysis.

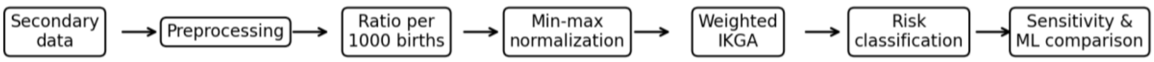

Figure 1. Research stages of the proposed IKGA framework

2.2 Data Sources and Indicators

The study used secondary district or city data. The number of births, severe malnutrition cases, and LBW cases were obtained from the North Sumatra Provincial Health Office. Sanitation indicators were derived from Riskesdas. Supporting socioeconomic and access variables were compiled from the research dataset and district level statistical records. Table 1 presents the operational definitions, units, data sources, annual availability, risk direction, and baseline weights of the indicators.

Table 1. Operational definition, source, and weight of IKGA indicators

Indicator	Operational definition	Unit	Source	Year	Risk	Weight
Severe malnutrition	Severe malnutrition cases standardized as a regional burden indicator	Cases per 1,000 births	North Sumatra Provincial Health Office	2021-2023	Positive	0.16
LBW	Low birth weight cases standardized across districts or cities	Cases per 1,000 births	North Sumatra Provincial Health Office	2021-2023	Positive	0.12
Family income	Average or categorical household income indicator	Score/IDR-based category	District level research dataset; BPS aligned statistical records	2021-2023	Negative	0.10
Unemployed household head	Household heads reported as unemployed	Percentage/score	District level research dataset; BPS aligned statistical records	2021-2023	Positive	0.08
Non-electric household	Households without electricity access	Percentage/score	District level research dataset; BPS aligned statistical records	2021-2023	Positive	0.07
Sanitation	Household sanitation or proper sanitation indicator	Percentage/score	Riskesdas-aligned indicator	2021-2023 aligned dataset	Negative	0.12

Jurnal Sistem Komputer dan Informatika (JSON)
Volume 7, Nomor 4, Juni 2026
e-ISSN 2685-998X
DOI 10.30865/json.v7i4.9785

Indicator	Operational definition	Unit	Source	Year	Risk	Weight
Clean water availability	Households with access to clean water	Percentage/score	District level research/statistical dataset; BPS aligned records	2021-2023	Negative	0.10
Dietary pattern	Household dietary pattern risk indicator	Score	District level research dataset	2021-2023	Positive	0.08
Low maternal education	Mothers with junior high school or lower education	Percentage/score	District level research/statistical dataset; BPS/Riskesdas aligned records	2021-2023	Positive	0.09
Health service access	Access to health facilities or services	Percentage/score	District level research dataset; Health Office/BPS aligned records	2021-2023	Negative	0.08

Positive-risk indicators indicate that higher values represent higher vulnerability. Negative-risk indicators indicate that higher values represent lower vulnerability; therefore, their normalized values were reversed before aggregation. This distinction separates health outcomes from vulnerability factors and clarifies the analytical role of each indicator.

2.3 Indicator Transformation and Normalization

Severe malnutrition and LBW were transformed into ratios per 1,000 births to enable comparison across districts or cities. The use of births as the denominator was based on the availability and consistency of district level denominator data across the three observation years. Ideally, severe malnutrition should be expressed per 1,000 measured children under five. Therefore, the ratio in this study is used as an administrative proxy for regional burden rather than as a direct prevalence estimate. This limitation was explicitly considered in the interpretation, especially for districts with small birth denominators.

Min-max normalization was applied separately for each observation year. Thus, the IKGA score in a given year represents the relative vulnerability position of a district or city compared with other districts or cities in the same year. The trend analysis is therefore interpreted as a change in relative provincial vulnerability position, not as an absolute increase or decrease in nutritional risk over time. If X_i denotes an indicator value, X_{min} denotes its minimum value, and X_{max} denotes its maximum value across districts or cities in the same year, positive-risk indicators were normalized using (1).

$$Z_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \quad (1)$$

For negative-risk indicators, higher values indicate lower vulnerability; therefore, the normalized risk score was reversed as shown in (2).

$$Z_i = \frac{X_{max} - X_i}{X_{max} - X_{min}} \quad (2)$$

All normalized values range from 0 to 1, where 0 indicates the lowest relative risk and 1 indicates the highest relative risk for the respective indicator [18][19][20][21][22].

2.4 Weighting Rationale,Composite Index and Risk Classification

The initial weights were assigned conceptually based on the proximity of each indicator to child nutrition vulnerability and their relevance in previous undernutrition studies. Health outcome indicators, sanitation, clean water, and socioeconomic factors were given higher weights because they directly represent nutritional burden or major determinants of child growth. The weighting structure was not treated as final expert validated weights; therefore, sensitivity analysis was conducted to examine whether moderate changes in weights substantially altered district rankings.

The Child Nutrition Vulnerability Index was computed using weighted linear aggregation. The weight W_j represents the relative contribution of indicator j, and Z_j represents the normalized risk score. The index is defined in (3).

Jurnal Sistem Komputer dan Informatika (JSON)
Volume 7, Nomor 4, Juni 2026
e-ISSN 2685-998X
DOI 10.30865/json.v7i4.9785

$$IKGA = \sum_{j=1}^{n} (w_j \times Z_j) \quad (3)$$

The IKGA score ranges from 0 to 1. A higher score indicates higher relative vulnerability compared with other districts or cities in the dataset. The 2023 IKGA was classified into three categories using tertiles: low, moderate, and high. This classification is relative to the distribution of the 33 districts or cities and should not be interpreted as an absolute national risk threshold.

2.5 Sensitivity Analysis, Expert Validation, and Model Comparison

Weight sensitivity was evaluated using two approaches. First, a one-at-a-time sensitivity test increased and decreased each indicator weight by 20%, while proportionally adjusting the remaining weights so the total remained equal to 1. Second, Monte Carlo simulation generated 3,000 random weight sets within ±20% of the baseline weights and recalculated the ranking. Stability was evaluated using Spearman rank correlation, mean rank change, top-10 overlap, and probability of remaining in the top-10 priority group.

An expert validation framework was prepared using a 1-5 rating scale for indicator relevance and weight feasibility. The validity metrics include item level content validity index (I-CVI) and Aiken's V [23] [24]. Because real expert scores were not yet collected, the validation table in this manuscript is presented as an illustrative framework, not as final empirical expert validation.

For machine learning comparison, Random Forest and Decision Tree were used as supervised classifiers to reproduce the 2023 IKGA categories. K-Means with $k=3$ was used as an unsupervised clustering method. Performance was evaluated using accuracy and macro-F1 for supervised and label-aligned clustering results; adjusted Rand index and silhouette score were also reported for K-Means [25][26][27][28] .

3. RESULT AND DISCUSSION

3.1 IKGA Score and Priority Areas in 2023

The 2023 IKGA calculation produced a mean score of 0.3486 across 33 districts or cities. The highest vulnerability score was observed in Nias (0.5573), while the lowest score was observed in Kota Binjai (0.1934). Table 2 shows the ten priority areas based on the highest IKGA values in 2023.

Table 2. Top ten priority areas based on IKGA 2023

Rank	District or city	IKGA	Risk Category
1	Nias	0.5573	High
2	Nias Selatan	0.5515	High
3	Toba	0.5415	High
4	Nias Barat	0.5413	High
5	Nias Utara	0.5352	High
6	Labuhan Batu Utara	0.4474	High
7	Mandailing Natal	0.4256	High
8	Tapanuli Selatan	0.4012	High
9	Padang Lawas	0.3940	High
10	Kota Gunungsitoli	0.3719	High

The priority list indicates that the Nias Islands dominate the high risk group, including Nias, Nias Selatan, Nias Barat, Nias Utara, and Kota Gunungsitoli. This pattern is scientifically meaningful because island districts may face structural constraints related to transportation, service distribution, household resources, and access to sanitation and clean water. These findings are consistent with previous studies that emphasize the role of WASH conditions, socioeconomic vulnerability, and regional inequality in child undernutrition [29][30][31][32][33][34].

Toba and Labuhan Batu Utara also appear in the top-10 list. However, their interpretation requires caution because small denominator values can inflate ratio based indicators. The calculation therefore requires data quality attention before the results are used for operational decision making. Table 3 summarizes the main data quality notes considered during interpretation.

Table 3. Data quality notes in IKGA calculation

Issue	Example/Source	Potential Effect	Handling in Interpretation
Small birth denominator	Some districts with very low birth counts in 2023	Inflated severe malnutrition or LBW ratio per 1,000 births	Verify with Provincial Health Office and interpret as priority for data checking

Jurnal Sistem Komputer dan Informatika (JSON)
Volume 7, Nomor 4, Juni 2026
e-ISSN 2685-998X
DOI 10.30865/json.v7i4.9785

Issue	Example/Source	Potential Effect	Handling in Interpretation
Zero or very low environmental values	Clean water or sanitation indicators in selected years	Extreme normalized risk score	Cross check variable definition and consider sensitivity analysis
Relative tertile classification	33 districts or cities in North Sumatra	Risk categories are provincial relative priorities, not national thresholds	State explicitly in methodology and discussion

3.2 Trend of IKGA from 2021 to 2023

Figure 2 presents the average IKGA trend from 2021 to 2023. The provincial mean changed from 0.3556 in 2021 to 0.3812 in 2022 and then declined to 0.3486 in 2023. This indicates that 2022 was the year with the highest average relative vulnerability, while 2023 showed an aggregate improvement.

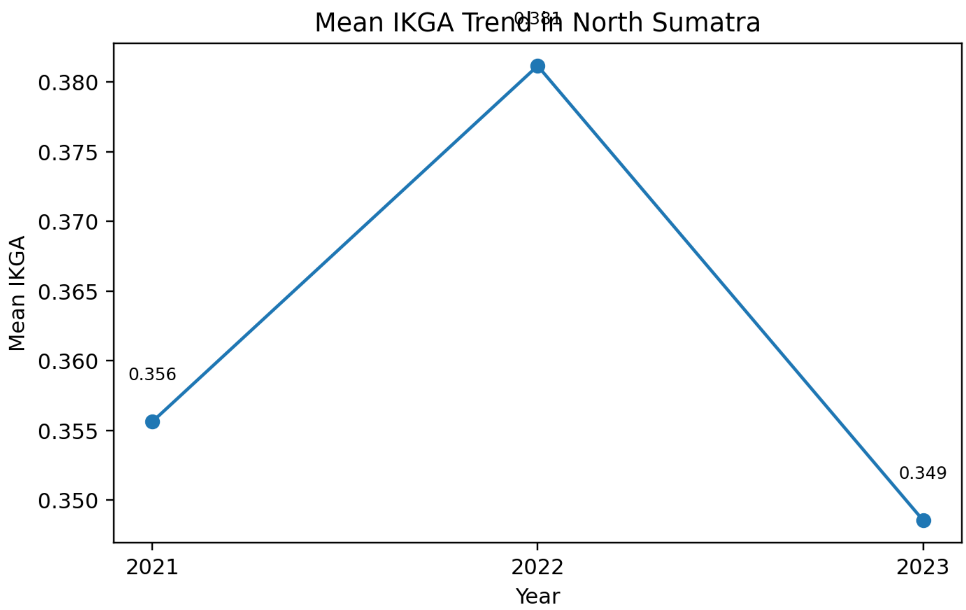

Figure 2. Average IKGA trend in North Sumatra from 2021 to 2023

Figure 3 shows the temporal trajectories for the ten priority areas in 2023. Several priority districts showed a declining trend after 2021 or 2022, but they remained relatively high compared with other districts or cities in 2023. This demonstrates that an area can improve over time while still requiring priority attention because its relative score remains among the highest in the province.

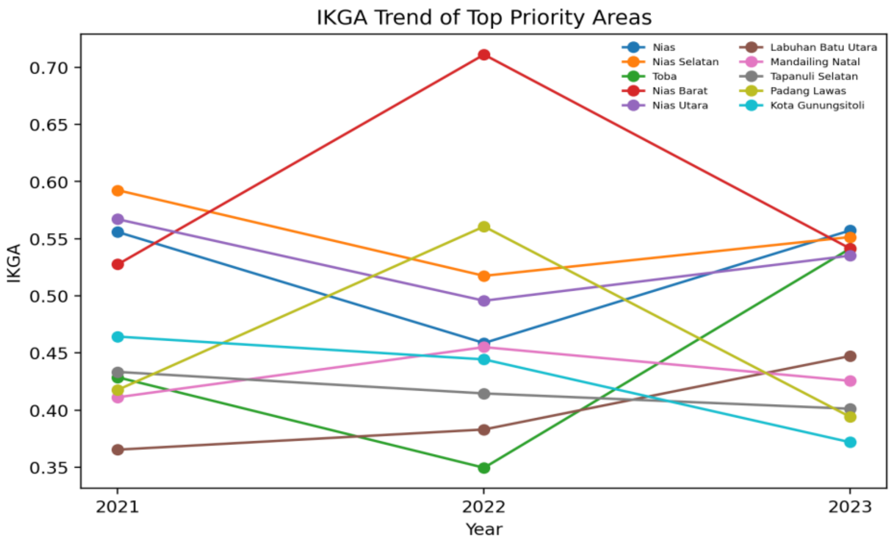

Figure 3. IKGA trend of the top priority areas from 2021 to 2023

Jurnal Sistem Komputer dan Informatika (JSON)
Volume 7, Nomor 4, Juni 2026
e-ISSN 2685-998X
DOI 10.30865/json.v7i4.9785

3.3 Spatial Distribution of Risk Categories

The 2023 classification produced a balanced distribution because tertile thresholds were used. Table 4 shows that 11 districts or cities were classified as high, 11 as moderate, and 11 as low. Figure 4 displays the point based spatial distribution using district or city coordinates.

Table 4. Distribution of IKGA risk categories in 2023

Risk Category	Number of Districts or Cities	Percentage
High	11	33.33
Moderate	11	33.33
Low	11	33.33

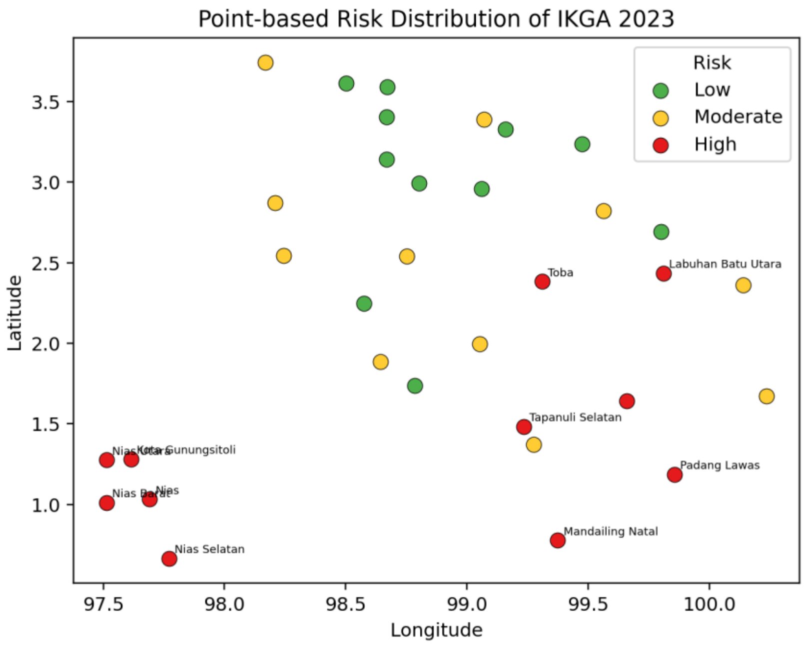

Figure 4. Spatial distribution of IKGA risk categories in 2023

The spatial pattern shows that high risk areas are not randomly dispersed. A concentration of high risk points appears in the Nias Islands and several other districts. The map is a point based visualization rather than an administrative boundary choropleth. For operational implementation, this map should be developed further using official district boundary shapefiles and integrated into a web based dashboard.

3.4 Weight Sensitivity Analysis

Sensitivity analysis was conducted to determine whether the priority ranking was robust to moderate changes in indicator weights. Figure 5 visualizes the mean rank change when each indicator weight was increased or decreased by 20%. Table 5 reports the scenarios with the largest effect on ranking stability.

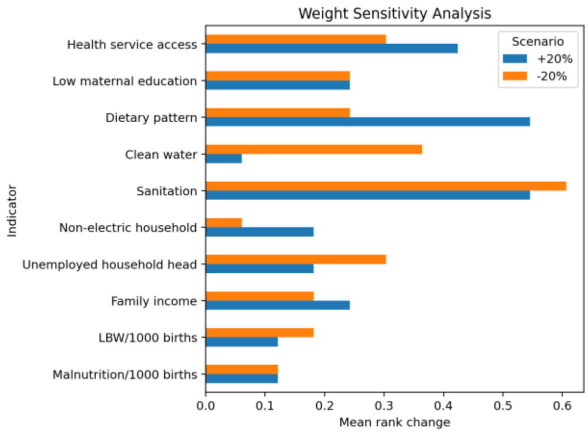

Figure 5. Sensitivity of IKGA ranking to 20% weight changes

Jurnal Sistem Komputer dan Informatika (JSON)
Volume 7, Nomor 4, Juni 2026
e-ISSN 2685-998X
DOI 10.30865/json.v7i4.9785

Table 5. Largest effects in the one-at-a-time weight sensitivity test

Indicator	Scenario	Spearman	Mean Rank Change	Maximum Rank Change	Top-10 Overlap
Sanitation	-20%	0.9940	0.61	4	10
Sanitation	+20%	0.9943	0.55	4	10
Dietary pattern	+20%	0.9957	0.55	2	9
Health service access	+20%	0.9967	0.42	2	10
Clean water	-20%	0.9977	0.36	2	10
Health service access	-20%	0.9973	0.30	3	10
Unemployed household head	-20%	0.9983	0.30	1	10
Family income	+20%	0.9983	0.24	2	10

The one-at-a-time sensitivity test showed high Spearman rank correlations in all scenarios. Monte Carlo simulation with 3,000 random weight sets produced an average Spearman correlation of 0.9957, with a minimum of 0.9860 and a maximum of 1.0000. These results indicate that the IKGA ranking is robust under moderate weight variation. Table 5 shows that the leading priority districts had high probabilities of remaining in the top-10 group under simulated weight changes.

Table 6. Monte Carlo ranking stability of the ten highest baseline districts

or	Baseline Rank	Mean MC Rank	SD MC Rank	Top-10 Probability
Nias	1	1.41	0.55	1.00
Nias Selatan	2	2.28	0.61	1.00
Toba	3	3.24	1.71	1.00
Nias Barat	4	3.50	0.52	1.00
Nias Utara	5	4.57	0.51	1.00
Labuhan Batu Utara	6	6.05	0.22	1.00
Mandailing Natal	7	6.95	0.22	1.00
Tapanuli Selatan	8	8.05	0.21	1.00
Padang Lawas	9	8.95	0.21	1.00
Kota Gunungsitoli	10	10.24	0.58	0.84

3.5 Machine Learning Comparison

Machine learning models were compared with the IKGA categories to evaluate whether data driven methods could reproduce the index based risk classification. Table 7 shows that Random Forest achieved the highest performance, followed by Decision Tree and K-Means. Figure 6 visualizes accuracy and macro-F1 across models.

Table 7. Performance comparison between supervised and unsupervised models

Model	Type	Accuracy	Macro-F1	ARI	Silhouette
Random Forest	Supervised	0.727	0.724	-	-
Decision Tree	Supervised	0.606	0.607	-	-
K-Means *(k=3)*	Unsupervised	0.455	0.366	0.071	0.396

Figure 6. Performance comparison of machine learning models

Jurnal Sistem Komputer dan Informatika (JSON)
Volume 7, Nomor 4, Juni 2026
e-ISSN 2685-998X
DOI 10.30865/json.v7i4.9785

Random Forest achieved an accuracy of 0.727 and macro-F1 of 0.724, indicating that it was the best model for reproducing the IKGA categories. Decision Tree produced lower but interpretable performance. K-Means showed weaker agreement with the IKGA categories, with a silhouette score of 0.396, suggesting that the natural cluster structure did not fully align with tertile-based risk classes. This result implies that supervised methods are more suitable than unsupervised clustering for reproducing the proposed IKGA category system.

To clarify classification behavior, Table 8 presents the cross-validated confusion matrix of the Random Forest model. The matrix shows that most low risk districts were correctly classified, whereas moderate and high categories had more boundary cases because tertile-based classes are relatively close to each other.

Table 8. Confusion matrix of the Random Forest classification

Actual / Predicted	Low	Moderate	High
Low	10	1	0
Moderate	3	7	1
High	1	3	7

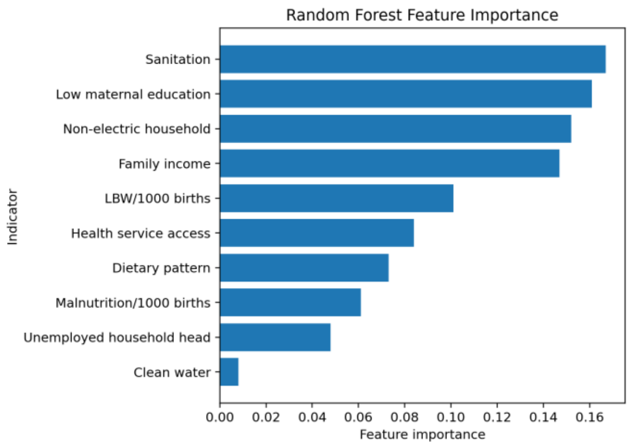

Figure 7. Feature importance of the Random Forest model

Feature importance analysis indicates which indicators contributed most strongly to the Random Forest classification. These findings can support interpretation of the IKGA framework and provide empirical input for refining weights. However, the sample size is limited to 33 districts or cities; therefore, machine learning results should be considered exploratory rather than definitive.

Table 9 lists the five most influential indicators identified by the fitted Random Forest model. These variables can be used as empirical input for refining the weighting structure in future versions of the index.

Table 9. Top five Random Forest feature importance values

Rank	Indicator	Importance
1	Sanitation	0.167
2	Low maternal education	0.161
3	Non-electric household	0.152
4	Family income	0.147
5	LBW per 1,000 births	0.101

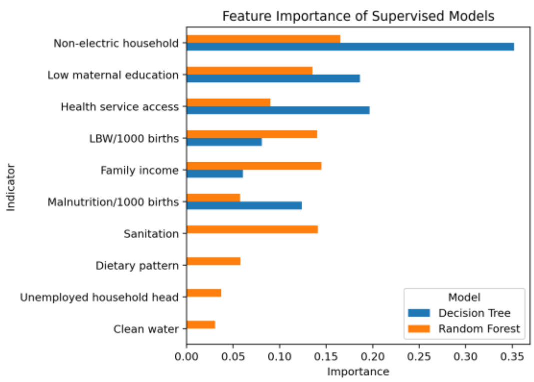

Figure 8. Feature importance of supervised machine learning models

Feature importance analysis indicates which indicators contributed most strongly to the supervised classification. These findings can support interpretation of the IKGA framework and provide empirical input for refining weights. However, the sample size is limited to 33 districts or cities; therefore, machine learning results should be considered exploratory rather than definitive.

3.6 Discussion and Policy Implications

The proposed IKGA demonstrates that child nutrition vulnerability is best understood as a combination of health burden, socioeconomic conditions, environmental factors, maternal education, dietary patterns, and service access. Districts with high scores generally do not only have high severe malnutrition or LBW ratios, they also tend to exhibit multiple contextual disadvantages. This supports the argument that intervention planning should integrate health and non health data rather than relying only on case counts.

The dominance of the Nias Islands in the high risk group suggests that accessibility and infrastructure should be considered when interpreting nutrition vulnerability. In island districts, health service distribution, transportation, household sanitation, and clean water access may be more constrained than in urban centers. This interpretation aligns with previous Indonesian studies showing that poverty, maternal education, sanitation, and regional context are associated with child undernutrition

The sensitivity analysis strengthens the methodological credibility of the index because the top priority districts remained stable under moderate weight changes. However, the use of conceptual weights remains a limitation. Future work should replace or refine the initial weights using expert validation and statistical procedures, such as principal component analysis, entropy weighting, or analytic hierarchy process, and should test whether revised weights improve interpretability and policy usefulness

From a policy perspective, the IKGA can support priority setting, field validation, and resource allocation. High risk districts can be prioritized for nutrition education, maternal child health monitoring, sanitation improvement, clean water programs, and strengthened referral access. Moderate risk districts should be monitored because changes in socioeconomic or environmental conditions may shift them into the high risk group. Low risk districts still require routine surveillance because relative improvement does not mean absence of risk.

The analysis also provides a foundation for SI-GIZI SIGAP. The index can become an analytic module that automatically calculates vulnerability scores, ranks districts, displays spatial patterns, and generates intervention priority lists. In future work, official administrative boundary maps, real expert validation, sensitivity adjusted weights, and longitudinal prediction models should be integrated to increase the operational value of the system.

This study has limitations. The classification is relative to the 33 districts or cities and should not be interpreted as an absolute risk category. Some ratios may be affected by small denominators, especially when the number of births is very low. The point based spatial map is descriptive and does not include formal spatial-autocorrelation testing. The expert validation component is still a framework and must be replaced with real expert scores. Finally, machine learning evaluation is limited by the small sample size and should be interpreted as exploratory benchmarking rather than conclusive predictive modeling.

4. CONCLUSION

This study developed the Child Nutrition Vulnerability Index (IKGA) as an interpretable composite index framework for mapping relative district level child nutrition vulnerability in 33 districts or cities of North Sumatra during 2021-2023. The index integrates health outcome indicators and vulnerability factors, including severe malnutrition, LBW, family income, unemployment, electricity access, sanitation, clean water, dietary pattern, maternal education, and health service access. In 2023, the highest relative vulnerability was observed in Nias, while the top-priority areas were dominated by districts in the Nias Islands, indicating the importance of spatially targeted nutrition intervention. Sensitivity analysis showed that the priority ranking was robust under moderate weight variation, with an average Spearman correlation of 0.9957 in the Monte Carlo simulation. Random Forest reproduced the IKGA categories better than Decision Tree and K-Means, but this result should be interpreted only as exploratory benchmarking because it used the same indicators and a small number of districts or cities. The proposed IKGA can support SI-GIZI SIGAP as a decision support tool for priority setting, but it should not yet be considered an absolute risk measure until the indicator weights are validated by experts, the data are verified with official sources, and the results are tested against independent nutritional outcomes.

ACKNOWLEDGMENT

The authors would like to thank the Lembaga Penelitian dan Pengabdian kepada Masyarakat (LPPM), Universitas Negeri Medan, for providing financial support through its research grant scheme. This support was essential for the implementation of the study. The authors also appreciate LPPM’s commitment to advancing scientific research and supporting initiatives that address regional public health challenges.

REFERENCES

[1] "Victora, C.G., Adair, L., Fall, C., Hallal, P.C., Martorell, R., Richter, L.M., et al. (2008) Maternal and Child Undernutrition Consequences for Adult Health and Human Capital. The Lancet, 371, 340-357. - References - Scientific Research Publishing." Accessed: May 08, 2026. [Online]. Available: https://www.scirp.org/reference/referencespapers?referenceid=2762043

[2] WHO, "World Health Organization Growth Standards," *Acta Paediatr.*, pp. 5–6, 2006, Accessed: May 08, 2026. [Online]. Available: http://www.who.int/childgrowth/standards/Technical_report.pdf?ua=1

[3] "Levels and trends in child malnutrition: UNICEF/WHO/World Bank Group joint child malnutrition estimates: key findings of the 2023 edition." Accessed: May 08, 2026. [Online]. Available: https://www.who.int/publications/i/item/9789240073791

[4] V. J. B. Matrins *et al.*, "Long-Lasting Effects of Undernutrition," *Int. J. Environ. Res. Public Health*, vol. 8, no. 6, p. 1817, 2011, doi: 10.3390/IJERPH8061817.

[5] X. Wang, B. Höjer, S. Guo, S. Luo, W. Zhou, and Y. Wang, "Stunting and 'overweight' in the WHO Child Growth Standards -malnutrition among children in a poor area of China," *Public Health Nutr.*, vol. 12, no. 11, pp. 1991–1998, Feb. 2009, doi: 10.1017/S1368980009990796.

[6] T. Beal, A. Tumilowicz, A. Sutrisna, D. Izwardy, and L. M. Neufeld, "A review of child stunting determinants in Indonesia," *Matern. Child Nutr.*, vol. 14, no. 4, p. e12617, Oct. 2018, doi: 10.1111/MCN.12617.

[7] F. Ramadhani, D. Septiana, S. N. Amalia, P. M. Fadilah, and A. Satria, "Spatial Clustering Analysis of Stunting in North Sumatra Based on Environmental Factors Using K-Means Algorithm," *Data Science: Journal of Computing and Applied Informatics*, vol. 9, no. 2, pp. 18–25, Jul. 2025, doi: 10.32734/JOCAI.V9.I2-17179.

[8] F. Ramadhani, S. I. Al-Idrus, D. Septiana, Arnita, D. R. Wahyuningrum, and Salamah, "Machine Learning-Based Risk Prediction and Spatial Mapping of Stunting in North Sumatra Using a Strategic Policy Approach," pp. 1–6, Jan. 2026, doi: 10.1109/ICCAI65301.2025.11278946.

[9] R. E. Caraka *et al.*, "Bayesian Network analysis of spatial disparities in child nutrition status and health determinants across Indonesia," *International Journal of Applied Earth Observation and Geoinformation*, vol. 144, p. 104936, Nov. 2025, doi: 10.1016/J.JAG.2025.104936.

[10] A. R. Nasution, A. Mardhiyah, and M. Rinaldi, "Exploration of development inequality models in north Sumatera," 2025. [Online]. Available: www.ijafibs.pelnus.ac.id

[11] K. A. Hutasuhut, L. M. Siahaan, and J. Hutasuhut, "Economic Convergence Among Urban Areas In North Sumatera," *Journal of Sustainable Economics*, vol. 3, no. 1, pp. 27–41, May 2025, doi: 10.32734/jse.v3i1.20286.

[12] V. Grigoriadis *et al.*, "Developing the Sus-Health Index: a combined measure for describing environmental impact and nutritive value of foods and meals," *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 380, no. 1935, p. 20240160, Sep. 2025, doi: 10.1098/RSTB.2024.0160.

[13] J. M. Bôto, B. Neto, V. Miguéis, and A. Rocha, "Development of the Dietary Pattern Sustainability Index (DIPASI): A novel multidimensional approach for assessing the sustainability of an individual's diet," *Sustain. Prod. Consum.*, vol. 50, pp. 139–154, Oct. 2024, doi: 10.1016/J.SPC.2024.07.029.

[14] C. Wehbe and H. Baroud, "Limitations and considerations of using composite indicators to measure vulnerability to natural hazards," *Scientific Reports 2024 14:1*, vol. 14, no. 1, pp. 19333-, Aug. 2024, doi: 10.1038/s41598-024-68060-z.

[15] M. Wanyonyi, Z. N. Morris, F. M. Musyoka, and D. M. Kitavi, "Enhanced machine learning and hybrid ensemble approaches for Coronary Heart Disease prediction," *PLoS One*, vol. 20, no. 12, p. e0328338, Dec. 2025, doi: 10.1371/JOURNAL.PONE.0328338.

[16] A. Podtschaske, B. Ulm, and S. Kagerbauer, "Pre-operative risk stratification from admission data: Clustering and KNN-modelling for identifying high risk patients before surgery," *J. Crit. Care*, vol. 92, p. 155376, Apr. 2026, doi: 10.1016/J.JCRC.2025.155376.

[17] M. Al Mahmud, S. Chowdhury, A. A. M. Hamim, and A. Haque, "Prevalence and determinants of low birth weight and its association with child malnutrition in Bangladesh," *BMC Nutr.*, vol. 12, no. 1, p. 76, Dec. 2026, doi: 10.1186/S40795-026-01291-7.

[18] K. Cabello-Solorzano, I. Ortigosa de Araujo, M. Peña, L. Correia, and A. J. Tallón-Ballesteros, "The Impact of Data Normalization on the Accuracy of Machine Learning Algorithms: A Comparative Analysis," *Lecture Notes in Networks and Systems*, vol. 750 LNNS, pp. 344–353, 2023, doi: 10.1007/978-3-031-42536-3_33/SAVE-RESEARCH.

[19] O. Mishkov, K. Zorin, D. Kovtoniuk, V. Dereko, and I. Morgun, "Comparative Analysis of Normalizing Techniques Based on the Use of Classification Quality Criteria," *Lecture Notes on Data Engineering and Communications Technologies*, vol. 77, pp. 602–612, 2022, doi: 10.1007/978-3-030-82014-5_41.

[20] Y. Sanggelorang, F. Ari Anggraini Sebayang, N. S. H. Malonda, and A. A. Rumayar, "Insights into Childhood Malnutrition: An Analysis on Food Vulnerability and Stunting using 2021 Indonesian Nutritional Status Survey Data," *Media Gizi Indonesia*, vol. 19, no. 3, pp. 282–290, Sep. 2024, doi: 10.20473/MGI.V19I3.282-290.

[21] H. Anastasia *et al.*, "Determinants of stunting in children under five years old in South Sulawesi and West Sulawesi Province: 2013 and 2018 Indonesian Basic Health Survey," *PLoS One*, vol. 18, no. 5 May, May 2023, doi: 10.1371/JOURNAL.PONE.0281962.

[22] M. R. Ara, "ASSESSMENT OF VULNERABILITY AND SUSTAINABLE LIVELIHOOD OF THE URBAN POOR: A STUDY IN KHULNA CITY CORPORATION, SOUTHWEST BANGLADESH," *Khulna University Studies*, pp. 217–228, Oct. 2022, doi: 10.53808/KUS.2017.14.1AND2.1702-S.

[23] D. F. Polit, C. T. Beck, and S. V. Owen, "Focus on research methods: Is the CVI an acceptable indicator of content validity? Appraisal and recommendations," *Res. Nurs. Health*, vol. 30, no. 4, pp. 459–467, Aug. 2007, doi: 10.1002/nur.20199.

[24] D. F. Polit and C. T. Beck, "The content validity index: are you sure you know what's being reported? Critique and recommendations," *Res. Nurs. Health*, vol. 29, no. 5, pp. 489–497, Oct. 2006, doi: 10.1002/NUR.20147.

[25] P. J. Rousseeuw, "Silhouettes: A graphical aid to the interpretation and validation of cluster analysis," *J. Comput. Appl. Math.*, vol. 20, no. C, pp. 53–65, Nov. 1987, doi: 10.1016/0377-0427(87)90125-7.

[26] T. Hastie, R. Tibshirani, and J. Friedman, "The Elements of Statistical Learning," 2009, doi: 10.1007/978-0-387-84858-7.

[27] F. Huettmann *et al.*, "Use of Machine Learning (ML) for Predicting and Analyzing Ecological and 'Presence Only' Data: An Overview of Applications and a Good Outlook," *Machine Learning for Ecology and Sustainable Natural Resource Management*, pp. 27–61, 2018, doi: 10.1007/978-3-319-96978-7_2.

[28] G. James, D. Witten, T. Hastie, and R. Tibshirani, "An Introduction to Statistical Learning with Applications in R Second Edition," 2021.

[29] H. Torlesse, A. A. Cronin, S. K. Sebayang, and R. Nandy, "Determinants of stunting in Indonesian children: evidence from a cross-sectional survey indicate a prominent role for the water, sanitation and hygiene sector in stunting reduction," *BMC Public Health 2016 16:1*, vol. 16, no. 1, pp. 669-, Jul. 2016, doi: 10.1186/S12889-016-3339-8.

[30] T. Mulyaningsih, I. Mohanty, V. Widyaningsih, T. A. Gebremedhin, R. Miranti, and V. H. Wiyono, "Beyond personal factors: Multilevel determinants of childhood stunting in Indonesia," *PLoS One*, vol. 16, no. 11, p. e0260265, Nov. 2021, doi: 10.1371/JOURNAL.PONE.0260265.

[31] A. D. Laksono, R. D. Wulandari, N. Amaliah, and R. W. Wisnuwardani, "Stunting among children under two years in Indonesia: Does maternal education matter?," *PLoS One*, vol. 17, no. 7 July, p. e0271509, Jul. 2022, doi: 10.1371/JOURNAL.PONE.0271509.

[32] C. R. Titaley, I. Ariawan, D. Hapsari, A. Muasyaroh, and M. J. Dibley, "Determinants of the Stunting of Children Under Two Years Old in Indonesia: A Multilevel Analysis of the 2013 Indonesia Basic Health Survey," *Nutrients 2019, Vol. 11, Page 1106*, vol. 11, no. 5, p. 1106, May 2019, doi: 10.3390/NU11051106.

[33] H. Anastasia *et al.*, "Determinants of stunting in children under five years old in South Sulawesi and West Sulawesi Province: 2013 and 2018 Indonesian Basic Health Survey," *PLoS One*, vol. 18, no. 5 May, p. e0281962, May 2023, doi: 10.1371/JOURNAL.PONE.0281962.

[34] A. Murad, F. Faruque, A. Naji, A. Tiwari, M. Helmi, and A. Dahlan, "Modelling geographical heterogeneity of diabetes prevalence and socio economic and built environment determinants in Saudi City - Jeddah," *Geospat. Health*, vol. 17, no. 1, Jun. 2022, doi: 10.4081/GH.2022.1055.