Jurnal Teknik Informatika (JUTIF)
P-ISSN: 2723-3863
E-ISSN: 2723-3871

Vol. 7, No. 1, February 2026, Page. 706-719
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.1.5474

A Hybrid Decision Support Framework for Food and Nutrition Security Assessment Using Multi-Criteria Decision Making and Machine Learning

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Received : Nov 26, 2025; Revised : Feb 9, 2026; Accepted : Mar 5, 2026; Published : Mar 7, 2026

Abstract

Food and nutrition security assessment requires an adaptive analytical approach due to the multidimensional and temporal complexity of food systems. This study proposes a hybrid decision support system integrating Multi-Criteria Decision Making (MCDM) methods, namely Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), with machine learning to evaluate and predict food security indicators dynamically. Panel data from West Java and East Nusa Tenggara for the period 2018–2024 were analyzed to capture structural and temporal characteristics. AHP was used to determine expert-based indicator weights, which were applied in TOPSIS to generate regional food security scores. These scores were subsequently modeled using machine learning with temporal feature engineering, including lag variables and rolling statistics, and evaluated using time-series cross-validation. The results reveal a strong negative correlation (−0.7398) between AHP weights and machine learning feature importance, indicating complementary expert-based and data-driven perspectives. Ridge Regression achieved the best predictive performance with an R^2 of 0.9983 on training data and 0.8186 under cross-validation. East Nusa Tenggara outperformed West Java in TOPSIS scores (0.4829 vs. 0.4626), highlighting the importance of food stability and utilization. This study advances Informatics by enabling dynamic and adaptive food security decision support.

Keywords : *AHP, Decision Support System, Food Security, Machine Learning, TOPSIS.*

1. INTRODUCTION

Food security and nutrition have become increasingly urgent global issues in the context of climate uncertainty, demographic pressures, and changes in food systems [1]. According to the Food and Agriculture Organization (FAO), food security is defined as a condition in which all people at all times have physical and economic access to sufficient, safe, nutritious food that meets their dietary needs and preferences for an active and healthy life [2]. However, numerous studies indicate that food security measurements and interventions are still hindered by the use of single indicators that only reflect one dimension (such as availability or access) and do not comprehensively address the dimensions of stability and utilization [3], [4].

Some literature suggests that conventional models and methods are inadequate to handle the complexity of food systems, including spatiotemporal characteristics, interactions between indicators, and external pressures (such as climate change and pandemics) [5], [6]. Therefore, an analytical framework and Decision Support System (DSS) capable of handling multiple variables, interconnections between indicators, and a range of historical data up to forecasting is needed.

In methodological studies, Multicriteria Decision Making (MCDM) methods such as the Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution

P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2026.7.1.5474

(TOPSIS) have been widely used to determine criterion weights and rank alternatives in strategic decision-making [7]. AHP allows expert evaluation through pairwise comparisons and systematic determination of criterion weights, while TOPSIS provides a ranking mechanism based on the distance from the ideal and anti-ideal solutions [8], [9]. However, the combined application of AHP and TOPSIS in the field of food security remains limited, particularly when attempting to integrate temporal dynamics and predictive capabilities.

On the other hand, the application of machine learning (ML) in food systems shows significant potential for prediction and understanding of complex patterns [10], [11]. Research on food security prediction in Malawi showed that the random forest model was able to rival conventional methods in capturing micro-level vulnerabilities [12]. A study that utilized data from the Food Security and Vulnerability Atlas (FSVA) to predict the National Food Security Index score using the XGBoost model achieved high performance with an $R^2 \approx 0.978$, although it still lacked the explicit integration of expert judgment weighting or indicator ranking systems [13]. This research emphasizes that data-driven models are capable of capturing historical patterns and making accurate predictions, but the main challenge is integrating these models with expert-based frameworks. However, despite ML's ability to capture large data patterns and nonlinear complexities, challenges such as limited data, model interpretability, and the lack of integration with expert decision frameworks have prevented optimal adoption [14]. Therefore, there exists a methodological gap between expert-based approaches (such as AHP) and data-driven methods in the context of food security. Additionally, research on the application of ML in food system management and food security has shown that this technology is still more focused on supply chains and risk management, with less integration of expert-weighted MCDM with ML predictive models into one comprehensive framework [15].

Previous studies also show that while various indicators have been identified, recent research still often uses one or two indicators and has not systematically addressed all four dimensions: availability, access, utilization, and stability [4], [14], [16]. This creates an opportunity for research that can integrate a comprehensive set of indicators, determine the relative weights between indicators based on expert judgment, and then test the relevance and validity of these weights through empirical data and predictive models.

This study offers a significant contribution in several aspects: (1) integrating an MCDM-based framework (AHP and TOPSIS) into a single DSS for food security and nutrition, weighted through expert surveys, (2) linking these weight results with empirical data analysis using the TOPSIS method, and (3) expanding the innovation by incorporating a machine learning module that performs feature engineering and predictive modeling on the TOPSIS scores, thus making the system adaptive and predictive. Therefore, this study is not only descriptive but also proactive in supporting data-driven and predictive policy in developing regions in Indonesia. The case study in Indonesian provinces further strengthens the empirical contribution and local-global significance of this system.

The main objective of this research is to design and test a Food Security and Nutrition Prediction Model, through an MCDM-based approach (AHP and TOPSIS) and the integration of machine learning. The study aims to answer the following research questions: How do experts prioritize the weights of food security indicators? To what extent does the TOPSIS score based on these weights reflect the empirical performance of each region? And how can the integration of machine learning improve predictive ability and synchronize expert weights with historical data patterns?.

2. METHOD

This study develops a hybrid decision support system (DSS) for food and nutrition security assessment by integrating Multi-Criteria Decision Making (MCDM) methods with machine learning for temporal analysis and prediction. The proposed framework combines expert-based weighting and

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ranking with data-driven modeling to address the multidimensional and dynamic nature of food security systems. The overall research workflow is illustrated in Figure 1, which presents the sequential process from data acquisition, indicator weighting, regional ranking, to predictive modeling and evaluation.

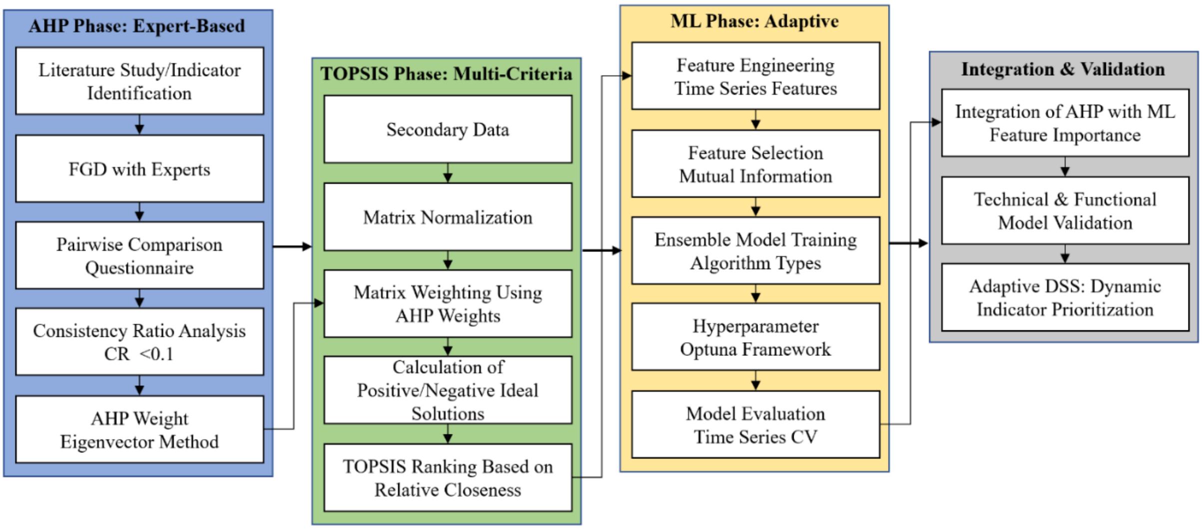

Figure 1. Proposed Hybrid Decision Support Framework for Food and Nutrition Security Assessment

2.1. Data Acquisition

Primary data were collected through a pairwise comparison questionnaire distributed to six expert respondents with the following qualifications: (1) a minimum of a Master's degree in Nutrition, Food Science, Food Technology, or Development Economics; (2) professional experience in research, policy formulation, or the implementation of food security programs; (3) a strategic position as decision-makers, heads of departments, or program coordinators. Respondents performed pairwise comparisons using a 1-9 Saaty scale for the four main pillars and their associated indicators [17]. The consistency of responses was validated using the Consistency Ratio (CR), with a threshold of < 0.1.

Secondary data includes 19 food security indicators from 2018 to 2024, obtained from the Central Statistics Agency (BPS), the Ministry of Health (Riskesdas, SSGI), the National Food Agency, and the Regional Development Planning Agency (Bappeda) of West Java and East Nusa Tenggara (NTT).

2.2. Analytic Hierarchy Process (AHP)

The AHP method was used to determine the relative weights of each food security indicator based on expert opinions. Using a questionnaire, respondents compared food security indicators within each dimension (availability, access, utilization, stability) using a Saaty scale of 1 to 9. The weights derived from this comparison process were used to measure the importance of each indicator. The pairwise comparison matrix generated from the questionnaire was processed using the eigenvector method to calculate relative weights, as explained in Equation (1), where aij is the relative comparison value between indicators i and j.

$$A = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ \frac{1}{a_{12}} & 1 & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ \frac{1}{a_{1n}} & \frac{1}{a_{2n}} & \dots & 1 \end{bmatrix} \tag{1}$$

The matrix was then normalized to produce standardized values. The criterion weights were determined as the principal eigenvector value, calculated from the row averages of the normalized matrix. Consistency validation was performed by calculating the Consistency Ratio (CR), which involves determining the maximum eigenvalue. CR was used to verify the consistency of the pairwise comparison matrix generated from the experts' responses. The formula for calculating the Consistency Index (CI) is shown in Equation (2). CR is then calculated by comparing CI with the Random Consistency Index (RI), which is fixed and depends on the number of criteria (n). RI is a constant taken from the Saaty table [18]. If the CR value is less than 0.1, the judgment is considered consistent and can be used for further processes. If CR is greater than 0.1, there is inconsistency in the judgment that needs to be corrected.

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{2}$$

2.3. Ranking with TOPSIS

After obtaining the weights from AHP, the next step is to use the TOPSIS method to rank the indicators based on their distance from the ideal and anti-ideal solutions. TOPSIS measures the performance of each alternative based on two main distances: the distance to the positive ideal solution (Equation 3) and the distance to the negative ideal solution (Equation 4). Vj- and Vj+ are the best and worst values of each criterion. The distance calculation process uses the weighted matrix Vij (Equation 5). W is the weight obtained from AHP, and Xij is the normalized value of the indicator. The TOPSIS score is calculated using Equation 6. A higher Ci value indicates better regional food security performance.

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (V_{ij} - V_j^+)^2} \tag{3}$$

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (V_{ij} - V_j^-)^2} \tag{4}$$

$$V_{ij} = w_j \,.\, X'_{ij} \tag{5}$$

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{6}$$

2.4. Machine Learning Integration

The integration of machine learning in this study is designed to enhance the predictive capabilities and adaptability of the model through comprehensive analysis of temporal patterns in historical data. The initial phase involves advanced feature engineering to capture the temporal dynamics of the food security system. We developed five categories of temporal features:

1. Lag features (TOPSIS_lag_[1,2,3]) to identify time dependencies.
2. Rolling statistics (mean, standard deviation, minimum, maximum with window [2,3]) to capture short-term volatility.
3. Exponential moving average (α = [0.3, 0.5, 0.7]) to track smoothed trends.
4. Temporal differences (TOPSIS_year_diff, TOPSIS_year_diff2) to measure acceleration of change.
5. Interaction features through the multiplication of priority indicators to capture synergistic effects between variables.

A comprehensive ensemble approach was implemented with ten strategically selected algorithms: (1) Random Forest Regressor with conservative parameters to avoid overfitting, (2) XGBoost, and (3) Gradient Boosting to handle non-linear relationships, (4) Bayesian Ridge Regression for stabilizing estimates, (5) Support Vector Regression to capture complex patterns, (6) Partial Least Squares

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Regression to handle multicollinearity, (7) Lasso and Ridge Regression for regularization, (8) Multi-Layer Perceptron for universal approximation, (9) Voting Regressor Ensemble for group wisdom aggregation, and (10) Optimized Random Forest through hyperparameter tuning.

Optimization was performed using the Optuna framework with 30 trials, resulting in the optimal configurations for Random Forest (n_estimators, max_depth, min_samples_split, min_samples_leaf), XGBoost (learning_rate, subsample, colsample_bytree), and Gradient Boosting (learning_rate, subsample).

2.5. Model Evaluation

Model evaluation and validation were conducted using 3-fold Time Series Cross-Validation, specifically designed for temporal data, with comprehensive evaluation using the R^2 metric (Equation 7) to measure predictive accuracy and generalization stability. Feature selection using SelectKBest with mutual_info_regression identified the most informative features, while comparative analysis between AHP weights and ML feature importance provided deep insights into the alignment between expert judgment and empirical data patterns in the complex food security system.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \check{y}_i)^2}{\sum_{j=1}^{n}(y_i - \check{y})^2} \qquad (7)$$

3. RESULT

3.1. AHP Phase: Expert-Based Weighting and Consistency Validation

The AHP process resulted in the weighting of food security indicators based on the evaluations from six experts, with the consistency of responses validated. All respondents showed Consistency Ratios (CR) < 0.1 (Table 1), indicating mathematically consistent expert judgments suitable for further analysis.

Table 1. AHP Respondent Consistency Validation Results

Respondent	CR	Consistency Status
1	0.0611	Consistent
2	0.0572	Consistent
3	0.0000	Consistent
4	0.0000	Consistent
5	0.0000	Consistent
6	0.0572	Consistent

The calculation results for the relative weights of the four main pillars of food security: Availability, Access, Utilization, and Stability are shown in Table 2 and the distribution of these weights in Figure 2. The weights assigned to the four pillars indicate a balanced distribution between supply-side dimensions (Availability: 29.01%) and demand-side dimensions (Access: 28.78%), with Utilization (20.92%) and Stability (21.28%) serving as significant supporting factors.

These weights reflect the importance of each pillar in the food security system, with Availability and Access holding larger weights compared to Utilization and Stability. The resulting weights indicate that Availability and Access are the two most influential factors in food security and nutrition, which aligns with previous findings that access to food and food supply are key factors in enhancing food security [19], [20].

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Table 2. Pillar Weight Results

Pillar	Weight
Availability	0.2901
Access	0.2878
Utilization	0.2092
Stability	0.2128

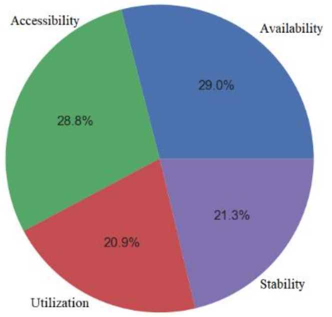

Figure 2. Distribution of Main Pillar Weights

The Availability and Access indicators are the primary factors affecting food security in developing regions, which leads to policies that focus more on improving access and food availability [21]. Other studies have found that in many developing countries, access to food and food availability are key determinants of food security levels [22]. These findings provide empirical insights into the relative importance of food security pillars, which may inform policy prioritization, particularly in regions with lower access and availability.

However, this study also reveals gaps in the dimensions of Utilization and Stability. Most previous studies tend to focus on Availability and Access, often overlooking aspects of Utilization and Stability, which can affect long-term food security. This study addresses this gap by introducing Utilization and Stability as critical factors in long-term food security. Figure 3 shows the top 10 priority food security indicators based on the AHP results. The global weight analysis reveals the Cereal Import Dependency Ratio (10.74%) as the indicator with the highest global weight, followed by Infrastructure Indicators (Ratio of Paved Roads to Total Roads: 9.42%) and Basic Access (Access to Improved Water Sources: 8.65%).

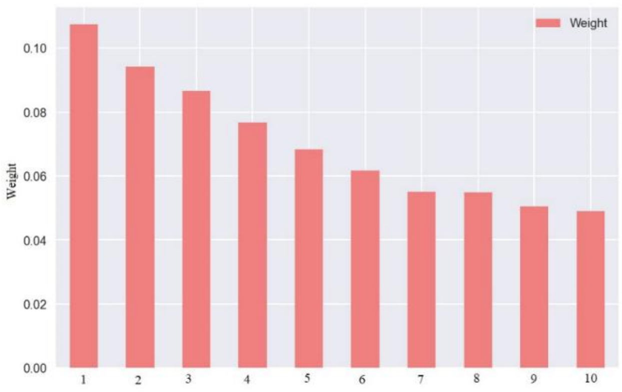

Figure 3. Graph of Global Weight Distribution for the Top 10 Food Security Indicators Based on AHP Results (1. Cereal Import Dependency Ratio, 2. Ratio of Paved Roads to Total Roads, 3. Access to Improved Water Sources, 4. Average Energy Sufficiency, 5. Domestic Food Price Index, 6. Average Protein Consumption, 7. Access to Improved Sanitation Facilities, 8. Percentage of Arable Land with Irrigation, 9. Value of Food Imports Compared to Food Exports, 10. Prevalence of Malnutrition)

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3.2. TOPSIS Phase: Multi-Criteria Ranking with AHP Weight Integration

After obtaining the weights using AHP, the next step is to use the TOPSIS method to rank food security indicators based on their distance from the ideal and anti-ideal solutions. Table 3 presents the TOPSIS score calculations for both provinces, showing significant differences in their food security scores. West Java in 2024 had a score of 0.4626, ranked 11th, while East Nusa Tenggara (NTT) scored 0.4829 and ranked 5th. This finding indicates that, although West Java excels in food access and availability, NTT performs better in food utilization and stability, which contributes to better food security in that province, highlighting the relative contribution of food stability and utilization dimensions to regional food security scores [23]. This demonstrates that factors such as food stability (the province's ability to withstand external shocks, such as climate change or food crises) and better utilization of available resources are more important for ensuring long-term food security, especially in more vulnerable areas. It is also important to emphasize that food security based on resilience to shocks and the utilization of local resources is crucial.

Table 3. TOPSIS Scores per Province (2024)

Province	TOPSIS Score	Rank
West Java (2024)	0.4626	11
East Nusa Tenggara (2024)	0.4829	5

Figure 4 shows the development of the TOPSIS scores for the two provinces from 2018 to 2024. The graph shows significant fluctuations in the TOPSIS scores for both provinces. West Java shows a relatively stable trend, although it experienced a sharp decline in 2020, followed by a slight recovery in subsequent years. In contrast, NTT exhibited greater variation, with a significant increase in 2023, reflecting a relatively rapid improvement in food security during that period. The peak in NTT in 2023 indicates significant progress in food security, which coincides with improvements in indicators related to food stability and utilization. This is consistent with the finding that food stability and resource utilization are dominant factors in the province's food security. Meanwhile, the more stable decline in West Java reflects instability in resource utilization or greater challenges in maintaining food security despite having better access to and availability of food. This highlights the long-term importance of food stability, indicating that food stability and utilization are more decisive factors in food security than access and availability directly [24].

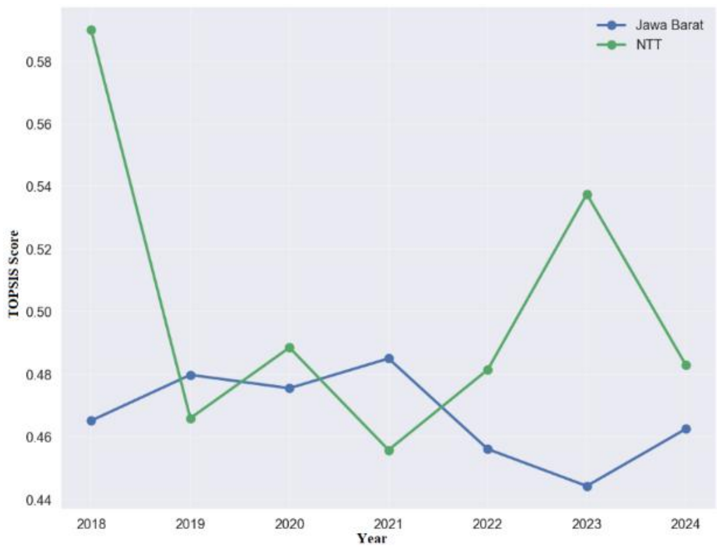

Figure 4. Graph of TOPSIS Score Development from 2018 to 2024

P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2026.7.1.5474

The distribution of TOPSIS scores per province (Figure 5) reveals that NTT has a wider range of scores, indicating higher variation in food security across years. This suggests more dynamic food security, likely influenced by external factors such as weather fluctuations or improved utilization of local resources. In contrast, West Java has a narrower distribution of scores, indicating greater stability in food security indicators, though with challenges in optimal utilization. Overall, this result shows that, while West Java excels in food access and availability, NTT exhibits stronger food security and better resilience in addressing challenges related to food stability and utilization. This offers valuable insights for policymakers to improve food stability and resource utilization in regions with better access and availability, such as West Java, and to enhance access to nutritious food in areas with stronger stability, like NTT.

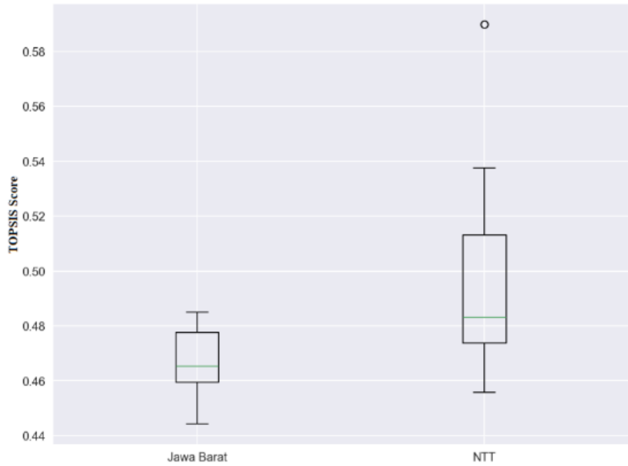

Figure 5. Distribution Graph of TOPSIS Scores per Province

3.3. Machine Learning Phase: Adaptive Optimization with Advanced Feature Engineering

3.3.1. Strategic Feature Engineering and Temporal Dynamics

The comprehensive feature engineering process successfully generated 58 potential features, with mutual information regression selecting the 15 most informative features. The dominance of temporal variables (73.3%) revealed that the food security system is more responsive to temporal dynamics than to the static levels of the indicators. As shown in Table 4, temporal features such as TOPSIS_rolling_mean_2, TOPSIS_lag_3, and TOPSIS_year_diff emerged as key determinants in the predictive pattern.

Table 4. Classification and Distribution of Selected Features Based on Mutual Information

Feature Category	Number of Features	Selected Features	Percentage
Temporal Features	11	TOPSIS_lag_3, TOPSIS_rolling_mean_2, TOPSIS_rolling_min_2, TOPSIS_rolling_max_2, TOPSIS_rolling_mean_3, TOPSIS_rolling_min_3, TOPSIS_rolling_max_3, TOPSIS_ema_0.3, TOPSIS_ema_0.5, TOPSIS_ema_0.7, TOPSIS_year_diff	73.3%
Static Indicators	3	Average Energy Sufficiency, Prevalence of Malnutrition, Access to Improved Sanitation Facilities	20%
Interaction Terms	1	Average Energy Sufficiency vs Average Protein Consumption	6.7%

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The dominance of temporal variables confirms previous findings that emphasize the importance of time-dependent patterns in complex food security systems [25]. Specifically, the presence of TOPSIS_lag_3 as a selected feature indicates that the current food security status is significantly influenced by the state of the system three years prior [26]. The rolling statistics configuration with varying windows (TOPSIS_rolling_mean_2, TOPSIS_rolling_mean_3) revealed that the food security system responds better to medium-term trends rather than short-term fluctuations. This finding supports adaptive governance theory, where food policies require the right timeframe to demonstrate effectiveness [27].

The presence of TOPSIS_year_diff as a critical feature confirms the importance of measuring the momentum of change rather than just absolute levels, as demonstrated in longitudinal studies [28]. This variable represents the acceleration or deceleration of the food security system, which is often more meaningful for policy than static positions. The selected interaction feature, Average Energy Sufficiency vs Average Protein Consumption, reveals a synergistic relationship between food consumption quantity and quality. Interestingly, from the initial 18 static indicators, only three passed the selection: Average Energy Sufficiency, Prevalence of Malnutrition, and Access to Improved Sanitation. This indicates that, although the AHP framework identified many important structural indicators, in the predictive-temporal perspective, only a small subset is truly informative. This finding suggests a shift from static indicator-based monitoring toward a more dynamic assessment approach that incorporates temporal patterns and interaction effects.

3.3.2. Comprehensive Evaluation of the Predictive Model and Overfitting Analysis

Comprehensive evaluation of ten machine learning algorithms revealed significant variations in performance when predicting the TOPSIS food security scores. As shown in Table 5, Ridge Regression ranked the highest with near-perfect training accuracy ($R^2 = 0.9983$) and excellent generalization ability (R^2 CV = 0.8186), followed by Bayesian Ridge (R^2 CV = 0.6423) as the runner-up.

Table 5. Benchmark Performance of Machine Learning Algorithms for Food Security Prediction

Algorithm	R^2 Training	R^2 Cross-Validation	RMSE	Status
Ridge	0.9983	0.8186	0.0015	Optimal
BayesianRidge	0.9997	0.6423	0.0006	Stable
PLS_Regression	0.9939	-8.4372	0.0028	Overfitting
GradientBoosting	0.9994	-2.0628	0.0009	Overfitting
XGBoost	0.9831	-16.1987	0.0047	Extreme Overfitting
Ensemble	0.9719	-2.3294	0.0061	Overfitting
RandomForest	0.7294	-1.0650	0.0189	Overfitting
Optimized_RandomForest	0.5652	-0.2986	0.0240	Underfitting
Lasso	0.0314	-0.3840	0.0358	Fail
MLP_Simple	-5.0178	-613.2519	0.0892	Fail

Analysis of the overfitting phenomenon revealed consistent patterns among complex models. XGBoost and Gradient Boosting showed extreme disparity between R^2 Training (0.9831 and 0.9994) and R^2 Cross-Validation (-16.1987 and -2.0628), indicating an inability of the models to generalize patterns beyond the training data. This phenomenon aligns with findings on the vulnerability of boosting algorithms to overfitting in datasets with limited dimensions and high noise levels [29]. The L2 regularization mechanism in Ridge Regression proved optimal in balancing the bias-variance tradeoff, resulting in minimal gaps between training and validation performance. Ridge Regression is particularly effective in regularized linear models for time-series data with limited dimensions [30]. The Bayesian Ridge model showed good stability (R^2 CV = 0.6423) despite lower computational complexity. These

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findings support the robustness of the Bayesian approach for inference in incomplete data conditions [31]. Conversely, the MLP_Simple model failed entirely with a negative R^2, confirming the mismatch of neural networks for very small datasets without advanced regularization techniques [32]. Ridge Regression was therefore selected as the final predictive model due to its superior generalization performance under time-series cross-validation.

The performance patterns of these algorithms provide methodological insights, indicating that in the context of food security with limited yet complex data, simpler models with appropriate regularization (Ridge, Bayesian Ridge) outperform more complex algorithms (XGBoost, MLP). This challenges the common assumption that more complex models are always superior [33].

4. DISCUSSIONS

The comprehensive integration of expert judgment based on AHP and data-driven patterns from machine learning reveals important and non-trivial insights into the complexity of food security systems. Correlation analysis identified a strong negative correlation coefficient (-0.7398) between AHP-derived weights and machine learning feature importance, a result that requires interpretation beyond descriptive statistical comparison. Rather than indicating inconsistency between methods, this divergence highlights the presence of distinct yet complementary analytical perspectives embedded within expert-based and data-driven approaches. Experts, through AHP, consistently prioritized long-term structural indicators, with the Cereal Import Dependency Ratio (10.74%) and the Ratio of Paved Roads (9.42%) as the most critical indicators. In contrast, ML identified temporal variables such as TOPSIS_rolling_mean_2 (20.01%) and TOPSIS_year_diff (8.64%) as the primary predictive drivers. This contrast suggests that while expert judgment emphasizes strategic, long-term determinants of food security, data-driven models capture short- to medium-term adaptive dynamics that may not be explicitly perceived through expert evaluation alone. These findings support the interpretation that expert-based and machine learning approaches are complementary rather than contradictory, as also observed in previous hybrid decision-making studies [34], [35]. In-depth analysis revealed that experts tend to think within a framework of structural resilience, prioritizing factors that build long-term resilience, such as infrastructure, import dependency, and basic access. Meanwhile, ML uncovered patterns of adaptive capacity, emphasizing the system's ability to respond to and adapt to short-term changes.

These results align with principles of complex adaptive systems theory, where food security systems are understood as dynamic entities characterized by non-linear interactions, feedback mechanisms, and temporal path dependence. Within this context, the proposed integration of MCDM and machine learning provides empirical support for a hybrid intelligence framework that combines deliberate, expert-driven strategies with emergent, data-driven patterns. Such an approach enables the simultaneous consideration of structural resilience and adaptive capacity in food security assessment [36].

From a technical perspective, the system demonstrated strong predictive performance, with a low RMSE value of 0.0015 and stable generalization, as indicated by an R^2 value of 0.8186 under time-series cross-validation. These results indicate that the proposed framework is capable of capturing temporal variations in food security while maintaining robustness under limited data conditions. At a functional level, the DSS highlighted differentiated regional dynamics: West Java exhibits relatively stable yet stagnating patterns that may benefit from interventions informed by temporal trend analysis, whereas East Nusa Tenggara (NTT) demonstrates higher variability and adaptive capacity, suggesting the importance of sustaining short-term responsiveness alongside improvements in structural indicators.

An important implication of this finding is that indicator prioritization within the DSS can shift over time, depending on system dynamics. Indicators with relatively lower expert-assigned weights may temporarily become influential leverage points, while structurally important indicators identified

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through expert judgment remain essential for long-term sustainability. This dynamic prioritization supports more context-sensitive and responsive policy analysis without undermining the role of expert knowledge.

The observed divergence between perceived importance and empirical influence is consistent with findings in related policy domains, such as climate adaptation and public health governance, where expert assessments do not always align with data-driven vulnerability patterns. Future research may explore advanced ensemble or alignment models that explicitly quantify and model the interaction between expert judgment and data-driven signals over time. Overall, the discussion underscores that the proposed hybrid decision support framework is not only methodologically feasible but also conceptually relevant for addressing the multidimensional and evolving challenges of food and nutrition security. By integrating expert knowledge with temporal data analytics, the framework contributes to the development of more adaptive and evidence-informed food security governance

5. CONCLUSION

This study successfully developed and validated an adaptive Decision Support System (DSS) that integrates Multi-Criteria Decision Making (MCDM) methods (AHP and TOPSIS) with machine learning for food and nutrition security assessment. The proposed hybrid framework demonstrates the value of combining expert judgment with data-driven temporal patterns in capturing the multidimensional and dynamic nature of food security systems. The observed strong negative correlation (-0.7398) between AHP-derived weights and machine learning feature importance does not indicate methodological inconsistency, but rather reflects complementary analytical perspectives. Experts tend to emphasize long-term structural resilience, while machine learning models capture short- to medium-term adaptive dynamics embedded in historical data.

From a predictive perspective, the superior performance of Ridge Regression (R^2 CV = 0.8186) confirms the suitability of regularized models for food security analysis under limited data conditions. The dominance of temporal variables (73.3% of selected features) further highlights the importance of incorporating temporal dynamics into food security assessment frameworks. In the regional comparison, East Nusa Tenggara (NTT) achieved higher TOPSIS scores than West Java (0.4829 vs. 0.4626), suggesting that adaptive capacity and stability-related factors play a significant role alongside access and availability in shaping regional food security outcomes.

Rather than prescribing direct policy actions, the findings suggest the relevance of differentiated analytical perspectives across regions. West Java may benefit from approaches that emphasize temporal trend analysis to address stagnation patterns, while NTT may require strategies that balance the maintenance of adaptive capacity with gradual strengthening of structural indicators. At a broader level, the integration of dynamic monitoring with expert-weighted structural indicators offers a promising analytical direction for national food security assessment.

This study is subject to several limitations, particularly related to data availability and temporal coverage, which constrain model complexity and generalization. Future research should expand the dataset across longer time horizons and additional regions, explore ensemble or hybrid models that explicitly quantify expert-data alignment, and evaluate the transferability of the proposed framework in different socio-economic contexts. Overall, this study contributes a methodologically grounded and adaptive decision support framework that advances food security assessment beyond static measurement toward more responsive and evidence-informed governance, with potential relevance for Indonesia and other developing regions pursuing food security–related Sustainable Development Goals.

CONFLICT OF INTEREST

The authors declares that there is no conflict of interest between the authors or with research object in this paper.

ACKNOWLEDGEMENT

This research was funded by the Ministry of Education, Culture, Research, and Technology (Kemdikbudristek) through the Research and Community Service Fund (DPPM) under contract number No. 125/C3/DT.05.00/PL/2025. The author expresses sincere gratitude for the financial support provided, which has enabled the successful completion of this research. Special thanks are also extended to the West Java Provincial Food Security Council (DKPP Jabar), the Bekasi City Food Security and Agriculture Office (DKPPP Kota Bekasi), and the other relevant departments for their valuable contributions and collaboration throughout the research process.

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