Bulletin of Information Technology (BIT)
Vol 7, No 3, September 2026, Hal. 359 – 366
ISSN 2722-0524 (media online)
DOI 10.47065/bit.v5i2.3069
https://journal.fkpt.org/index.php/BIT

Explainable Machine Learning for Post-Disaster Stunting Risk Prediction to Support Emergency Nutrition Decision-Making

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Abstract- Stunting risk in children under five rises sharply after disasters, as food-supply disruption, damaged health infrastructure, and degraded sanitation compound existing vulnerabilities. In evacuation centers, delayed identification of high-risk children stalls targeted emergency nutrition response. This study develops an explainable machine learning (XAI) system for post-disaster stunting risk prediction, combining an ensemble-based predictive model with SHapley Additive exPlanations (SHAP) to make risk scoring transparent and auditable for field decision-making. The model uses twelve anthropometric and sociodemographic features — including height-for-age (HAZ) and weight-for-age (WAZ) z-scores, exclusive breastfeeding, food intake frequency, immunization status, household sanitation, family income, and displacement duration — drawn from child victim data across Aceh, North Sumatra, and West Sumatra, supplemented by records from the Center for Disaster Management (CDC) and Indonesia's National Disaster Management Agency (BNPB). Performance was evaluated with stratified ten-fold cross-validation using AUC-ROC, F1-score, precision, and recall, and the model demonstrated strong and consistent discriminative ability in distinguishing high-risk from low-risk children despite class imbalance in the disaster-affected dataset. SHAP-based interpretability analysis identified HAZ z-score, displacement duration, food intake frequency, exclusive breastfeeding, and sanitation conditions as the five most influential predictors, consistent with established nutrition-science risk factors, while also revealing that prolonged displacement compounds the effect of inadequate food intake and poor sanitation, producing a disproportionately higher risk profile than any single factor alone. These explanations are delivered through a web-based decision-support interface showing per-child SHAP force plots and population-level summary plots, allowing field nutrition workers without data-science training to interpret the rationale behind each risk prediction. The resulting framework offers the Ministry of Health, BNPB, and humanitarian agencies a transparent, auditable, and field-deployable tool for prioritizing emergency nutrition intervention after disasters.

Keywords: xplainable Machine Learning; Stunting Prediction; Ensemble Learning; Emergency Nutrition; Decision Support System

1. INTRODUCTION

Stunting is a condition of growth failure in children due to chronic malnutrition characterized by height below minus two standard deviations based on WHO growth standards. This condition is one of the most serious forms of malnutrition because it impacts not only physical growth, but also cognitive development, increasing the risk of chronic diseases, decreasing economic productivity, and perpetuating intergenerational poverty [1]. UNICEF, WHO, and WFP report that approximately 148 million children under five worldwide will experience stunting in 2022, making it one of the main challenges for global public health [2]. In Indonesia, the prevalence of stunting has decreased from 37.2% in 2013 to 21.6% in 2023, but this figure is still above the WHO threshold of 20% and the 2024 RPJMN target of 14% . In addition, the distribution of stunting in Indonesia remains uneven, especially in Eastern Indonesia, Nusa Tenggara, and remote island areas which recorded a prevalence above 30%. These conditions indicate that Indonesia remains vulnerable to an increase in stunting prevalence, particularly when there are major disruptions to food systems and health services due to natural disasters.

Indonesia is one of the countries with the highest disaster risk levels in the world, with more than 2,000 natural disasters annually, including earthquakes, tsunamis, floods, landslides, volcanic eruptions, and extreme droughts [3]. Post-disaster situations often force people to live in refugee camps with limited infrastructure for food, sanitation, clean water, and health services. These conditions create risk factors that can accelerate stunting, such as disrupted access to nutritious food, interruptions in primary health care and immunization programs, deteriorating environmental sanitation, increased infectious diseases, disruptions to breastfeeding, and interruptions in the distribution of nutritional supplements [4], [5]. Previous research has shown that the prevalence of acute malnutrition in refugee camps can increase two- to fivefold in the first 60 days after a disaster. Furthermore, children who remain in refugee camps for more than 90 days have a risk of stunting up to 3.4 times higher than in normal conditions [6]. A similar phenomenon was also found in the 2018 Lombok earthquake and Palu-Donggala tsunami, where stunting prevalence increased two- to threefold in the first three months after the disaster [7].

In this context, conventional nutritional risk identification systems still face various limitations. Methods such as Mid-Upper Arm Circumference (MUAC), complete anthropometric measurements, and the Screening Tool for Identification of Malnutrition in Pediatrics (STAMP) require trained personnel, specialized measuring instruments, and relatively long examination times [8], [9]. In mass evacuation settings, these limitations lead to delays in the screening process and the distribution of poorly targeted nutritional interventions. Furthermore, conventional approaches tend to be reactive because identification is carried out after clinical symptoms of malnutrition appear. However, research shows that nutritional interventions in the early stages of nutritional deterioration are four to six times more effective than interventions after

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stunting has already occurred [10]. Therefore, a predictive approach is needed that can identify stunting risk earlier and more accurately.

The development of machine learning (ML) and artificial intelligence opens new opportunities in the development of multivariable and non-linear stunting risk prediction models. Several studies have shown that ML algorithms perform better than conventional statistical methods. Hasan et al. [11], [12], [13] reported that a Random Forest model based on Indonesian RISKESDAS data achieved an AUC-ROC of 0.88, higher than conventional logistic regression with an AUC-ROC of 0.74. Tiruneh et al. [14], [15] found that the Gradient Boosting algorithm provided the best performance in stunting prediction with an F1-Score of 0.87. Meanwhile, Picot et al. [16], [17], [18] showed that deep neural networks were able to identify stunting risk up to six months before clinical manifestations appeared. However, most of these studies still used normal population data and produced black-box models that were difficult to explain to non-technical users [19]. These limitations become obstacles in implementing prediction systems in disaster situations that require transparency and interpretability of results.

To address these limitations, the concept of Explainable Artificial Intelligence (XAI) was developed to improve the interpretability of ML models. One of the most widely used XAI methods is SHapley Additive Explanations (SHAP), which can explain the contribution of each feature to prediction results at both the individual and population levels [20], [21]. The integration of SHAP enables prediction systems to not only generate risk scores but also provide explanations of the dominant factors influencing those predictions. This approach can increase user confidence, support more targeted intervention decisions, and meet auditability needs in health and humanitarian programs [22].

Based on a literature review, several research gaps remain unanswered. First, there is no stunting prediction model that specifically utilizes post-disaster contextual features such as evacuation duration, disruption of food access, and sanitation degradation as key variables [23]. Second, the implementation of XAI to support field users in emergency nutrition contexts is still very limited [24]. Third, previous research rarely integrates ML models, XAI, and Decision Support Systems (DSS) into a single operational system that can be used directly by field officers [25]. Fourth, the use of primary datasets from post-disaster refugee camps in Indonesia in ML-based stunting prediction research is still very limited [26].

To address this gap, this study developed an Explainable Machine Learning-based post-disaster stunting risk prediction system called EML-StuntingPredict. This system uses ensemble learning algorithms such as Random Forest, XGBoost, and LightGBM, trained on primary datasets from post-disaster refugee camps in Indonesia. Furthermore, this study integrated the SHAP method to generate predictive interpretations at the local and global levels, conducted an ablation study to measure the contribution of each feature group to model performance, and developed a web-based Decision Support System prototype that can be used by field nutrition workers without requiring technical expertise in data science.

2. RESEARCH METHODOLOGY

2.1 Research Framework

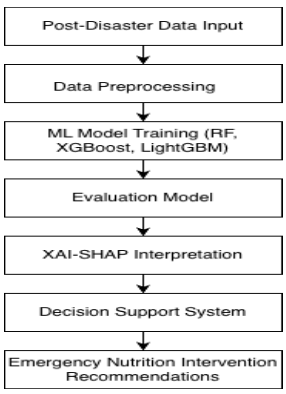

Figure 1. Research Framework

In the context of the research on a Post-Disaster Stunting Risk Prediction System Based on Explainable Machine Learning to Support Emergency Nutrition Intervention Decisions, the model integrates machine learning approaches, Explainable Artificial Intelligence (XAI), and decision support systems to produce an accurate, interpretive, and applicable post-disaster stunting risk prediction system. The development of this model is based on the need for an early identification system for stunting risk that can work in refugee conditions with limited resources, while providing explanations that are easy to understand for field nutrition officers and decision-makers.

This research model was developed through several key, interconnected stages, starting with post-disaster data collection, data preprocessing, machine learning-based prediction model development, interpretation of prediction results using the SHAP method, and implementation of a web-based decision support system. A machine learning approach was used to model the complex relationships between multivariable and nonlinear stunting risk variables, while the XAI method with

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SHAP was applied to increase the transparency and interpretability of the model's prediction results. Thus, the developed system not only generates stunting risk levels but also explains the dominant factors influencing predictions for each individual child and the population.
Furthermore, this research model is designed to support rapid and targeted decision-making for emergency nutrition interventions in post-disaster situations. The integration of SHAP prediction results and visualizations into a Decision Support System (DSS) enables field officers to obtain data-driven intervention recommendations in real-time without requiring technical expertise in data science or artificial intelligence. Therefore, the proposed research model is expected to contribute to the development of an explainable machine learning-based health prediction system that is adaptive, transparent, and implementable in the disaster context in Indonesia.

For an f model with p features, the Shapley value of feature i in sample x is defined as:

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

Component interpretation:

Symbol	Meaning in the Stunting Context
F	The set of all 12 input features (HAZ, WAZ, exclusive breastfeeding, sanitation, etc.)
S	A subset of features that excludes feature i
ϕ_i	The contribution of feature i to the prediction of an individual child
$f_{S\cup\{i\}}(x) - f_S(x)$	The marginal contribution of feature i when added to coalition S
$\frac{\|S\|!(\|F\|-\|S\|-1)!}{\|F\|!}$	The averaging weight over all possible orderings in which feature i can be added to the coalition

SHAP equation :

$$f(x_i) = E[f(x)] + \sum_{j=1}^{12} \phi_j(x_i) \tag{2}$$

SHAP Absolute value average :

$$\bar{\phi}_j = \frac{1}{N} \sum_{i=1}^{N} |\phi_j(x_i)| \tag{3}$$

2.2 Research Stages

The research model for a Post-Disaster Stunting Risk Prediction System Based on Explainable Machine Learning to Support Emergency Nutrition Intervention Decisions utilizes an integrated framework that combines field data collection, machine learning modeling, Explainable Artificial Intelligence (XAI) interpretation using the SHAP method, and a web-based decision support system. This model aims to generate early and interpretive stunting risk predictions for children in post-disaster evacuation sites, thereby assisting nutrition workers in quickly and accurately prioritizing interventions.
Conceptually, the research model consists of five main stages: data collection, data preprocessing, predictive model development, model interpretation using SHAP, and Decision Support System (DSS) implementation. During the data collection stage, the study utilized primary datasets obtained from post-disaster evacuation sites in Indonesia. The variables collected included child anthropometric data (height, weight, age, and MUAC), medical history, immunization status, nutritional intake patterns, sanitation conditions, access to clean water, duration of evacuation, family socioeconomic conditions, and access to health services and food aid. These variables were selected because they represent both biological and contextual risk factors for stunting in post-disaster situations.
The next stage was data preprocessing, which included data cleaning, handling missing values, feature normalization, encoding categorical variables, and feature selection using feature importance and correlation techniques. The dataset was then divided into training and testing data to build a predictive model. In the model development stage, the study employed an ensemble learning approach using the Random Forest, XGBoost, and LightGBM algorithms. These three algorithms

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were selected because of their high capability in handling non-linear and multivariable data and their proven performance in previous health prediction studies. Model evaluation was conducted using Accuracy, Precision, Recall, F1-Score, and AUC-ROC metrics to determine the best model for predicting post-disaster stunting risk.
Once the best model was obtained, the study integrated Explainable Artificial Intelligence (XAI) methods using SHapley Additive exPlanations (SHAP). The SHAP method is used to explain the contribution of each feature to the model's prediction results at both the local and global levels. Local explanations were used to identify the dominant factors predicting a child's high risk of stunting, while global explanations were used to identify patterns of key risk factors across the refugee population as a whole. The SHAP visualizations used included summary plots, dependence plots, force plots, and waterfall plots. The SHAP integration aimed to increase model transparency so that the prediction results could be understood and trusted by nutrition officers and policymakers.
The final stage of the research was the implementation of a web-based decision support system that integrates machine learning prediction results and SHAP visualizations. This system was designed for simple use by field nutrition officers through an interface that displays the stunting risk level, dominant causal factors, and recommendations for emergency nutrition interventions based on health protocols. Thus, this research model functions not only as a prediction system but also as an adaptive, interpretive, and applicable decision-making tool in post-disaster situations.

3. RESULT AND DISCUSSION

3.1. System Development and Implementation

This research successfully developed a web-based Post-Disaster Stunting Risk Prediction System, named NutriSiaga, using an Explainable Machine Learning approach. The development process was conducted by integrating data management, machine learning-based risk prediction, Explainable Artificial Intelligence (XAI), and nutrition intervention recommendations into a single information system. The development was designed to address the operational challenges of post-disaster nutrition response, where field officers require rapid access to toddler health information and interpretable risk assessments for intervention prioritization.
The implementation process consisted of several sequential activities, beginning with the preparation and management of toddler and post-disaster location data, followed by the input of anthropometric, health, and environmental variables. The prepared data were then processed by the machine learning prediction component to generate an individual stunting risk score and risk category. The prediction output was subsequently interpreted using the SHapley Additive exPlanations (SHAP) method to identify the contribution of individual predictor variables. Finally, the prediction and interpretation results were connected to an intervention recommendation component to provide practical information for field officers. This process establishes an integrated workflow from data collection and measurement to prediction, explanation, and intervention support.
Based on the implementation results, the NutriSiaga prototype successfully provided the principal functions required for post-disaster stunting risk monitoring. These functions include user authentication, dashboard monitoring, evacuation site management, toddler data administration, anthropometric measurement input, machine learning prediction, SHAP-based interpretation, and nutrition intervention recommendations. The system was implemented as a web-based platform and can be accessed through commonly used modern web browsers, including Google Chrome and Microsoft Edge.

3.2. Post-Disaster Monitoring Dashboard

The main dashboard was developed to provide a rapid overview of the nutritional risk conditions of toddlers across evacuation sites. The dashboard presents Key Performance Indicators (KPIs), stunting risk distribution, inspection activity logs, and geospatial information related to evacuation posts. The risk distribution categorizes toddlers into low-, medium-, and high-risk groups, enabling field officers to identify priority groups without having to examine individual records sequentially.
The geospatial monitoring component further supports area-level assessment by displaying the distribution of evacuation posts and identifying locations requiring greater attention. Areas with a concentration of high-risk toddlers can therefore be prioritized for further assessment and intervention. This functionality is particularly relevant in post-disaster settings because limited personnel, disrupted infrastructure, and restricted access may require nutrition resources to be allocated according to the level of observed risk.
The implementation demonstrates that the dashboard transforms individual prediction outputs into aggregated information that can support operational monitoring. Thus, the system provides two complementary perspectives: individual-level risk identification and location-level monitoring. These capabilities strengthen the potential use of the system as a decision-support tool rather than merely as a prediction application.

3.3. Toddler Data and Measurement Management

The toddler administration module was implemented to manage individual records, including identity information, age, evacuation location, and basic health-related information. The registration process links each toddler to the corresponding evacuation site, allowing individual risk information to be associated with a specific post-disaster location.

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Data validation and structured input mechanisms were incorporated to reduce duplicate records and improve the consistency of information entered by field officers.

The measurement module subsequently collects variables required by the prediction process. These include body weight, height or length, mid-upper arm circumference (MUAC), history of diarrhea, availability of clean water, and food access during the previous 24 hours. Figure 2 illustrates the measurement input interface, while Figure 3 presents the resulting prediction output.

The implemented workflow can be expressed as:

Toddler Registration → Measurement Input → Data Processing → Risk Prediction → SHAP Interpretation → Intervention Recommendation.

This workflow represents an important implementation outcome because it connects routine field data collection with analytical processing within the same system. Consequently, field officers do not need to perform separate manual calculations or transfer data between independent applications before obtaining a risk assessment.

3.4. Machine Learning-Based Stunting Risk Prediction

The prediction module processes the available anthropometric, health, and environmental information to generate a stunting risk assessment for each toddler. The prediction process begins when the required measurement and contextual variables have been entered and validated. The processed variables are then submitted to the trained machine learning model, which produces a risk score and corresponding risk category.

The implementation successfully demonstrated the integration of the machine learning component with the information system interface. Rather than presenting the machine learning model as an independent computational component, its output is directly returned to the user through the NutriSiaga interface. This integration enables the prediction process to become part of the operational workflow used by field officers.

However, the successful implementation of the prediction function should be distinguished from the statistical performance of the machine learning model. The present system testing confirms that the prediction workflow can be executed and integrated into the application, whereas quantitative model performance should be assessed using independent evaluation metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). In the context of emergency nutrition, recall for the high-risk category is particularly important because failure to identify a genuinely high-risk toddler may result in delayed intervention.

3.5. Explainability Using SHAP

A major contribution of the proposed system is the integration of Explainable Artificial Intelligence through SHapley Additive exPlanations (SHAP). Conventional machine learning prediction systems may provide a classification result without explaining why an individual is categorized as being at a particular risk level. NutriSiaga addresses this limitation by generating an individual-level explanation of the prediction.

After the machine learning model generates a risk prediction, SHAP is applied to quantify the contribution of each input variable to that prediction. The resulting explanation is presented through a SHAP bar chart, enabling users to distinguish variables that contribute to increasing or decreasing the predicted risk. In the implemented interface, factors associated with increased risk are presented in red, whereas factors associated with reduced risk are displayed in green.

This process improves the interpretability of the prediction because field officers can move beyond the question of "What is the risk?" to "Why is this toddler classified at this risk level?" For example, the contribution of anthropometric measurements, recent illness history, food access, or water availability can be examined in relation to the individual prediction. Such information is particularly valuable in post-disaster settings, where interventions need to address the underlying risk factors rather than relying solely on a categorical prediction.

The SHAP implementation therefore changes the role of the system from a conventional black-box prediction tool into an interpretable decision-support system. Nevertheless, SHAP explanations should be interpreted as explanations of the machine learning model's predictions rather than as direct evidence of clinical causality. The identified variables indicate their contribution to the model output and should be considered together with professional assessment and field conditions.

3.6. Automated Nutrition Intervention Recommendations

Following the prediction and explanation stages, NutriSiaga provides automated nutrition intervention recommendations according to the identified risk level. The recommendation component links analytical results with potential operational responses, including supplementary feeding (PMT), referral to a field hospital, and sanitation and environmental health education.

The integration of prediction, explanation, and recommendation provides a complete decision-support workflow:

Risk Identification → Risk Explanation → Intervention Prioritization → Recommended Response.

This integration represents an important improvement over systems that only provide a prediction score. In emergency situations, the practical value of a predictive system depends not only on its ability to identify risk but also on its ability

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to translate analytical information into actionable priorities. The recommendation component therefore provides an initial bridge between machine learning outputs and emergency nutrition response.

The recommendations should, however, be regarded as decision-support information rather than autonomous clinical decisions. Final intervention decisions remain dependent on assessment by qualified health and humanitarian personnel, local protocols, resource availability, and the specific conditions of each evacuation site.

3.7. System Testing and Level of Success

Functional implementation and testing demonstrated that the major components of NutriSiaga could be integrated into a single operational workflow. The system was able to perform the core functions of user authentication, evacuation site management, toddler registration, measurement data input, risk prediction, SHAP-based explanation, and intervention recommendation. These results indicate a successful achievement of the primary objective of the prototype development, namely establishing an integrated digital platform for post-disaster stunting risk identification and nutrition response support.

The level of success of the current research can therefore be assessed from three implementation dimensions. First, functional success was achieved because the principal system modules and prediction workflow were successfully implemented. Second, analytical success was demonstrated through the successful integration of the machine learning prediction component and SHAP-based interpretation. Third, decision-support success was demonstrated through the connection between risk assessment and automated nutrition intervention recommendations.

Nevertheless, the current results primarily demonstrate the functional and prototype-level feasibility of the proposed system. A definitive assessment of predictive effectiveness requires quantitative model evaluation using a sufficiently representative dataset and independent testing data. Similarly, the practical effectiveness of the system should be further evaluated through usability testing and field-based validation involving health workers or humanitarian personnel. These evaluations are important to determine whether the system can maintain its effectiveness under real post-disaster conditions.

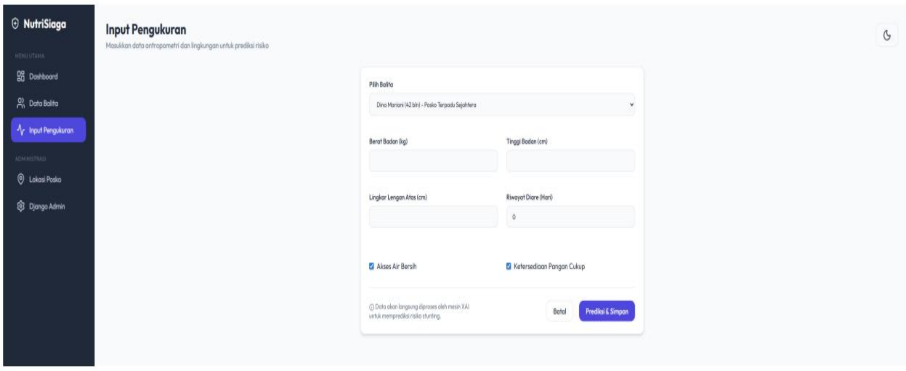

Figure 2. Measurement Input

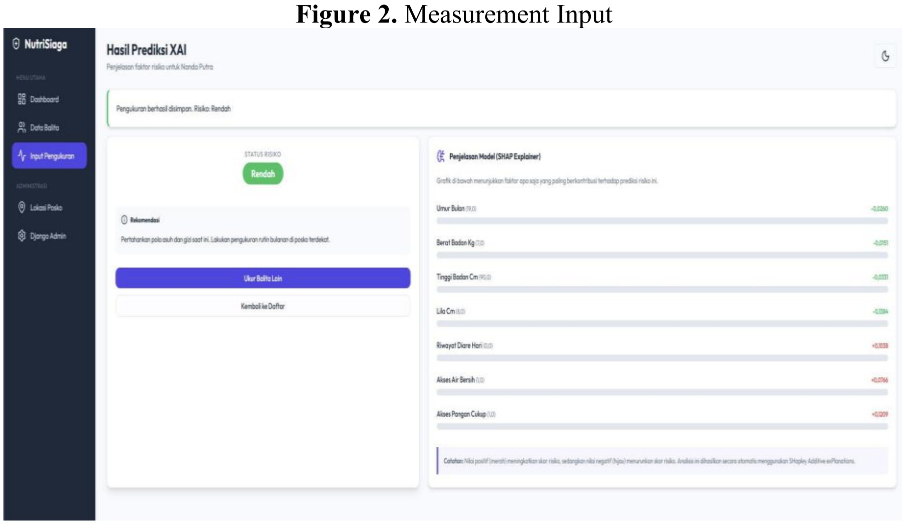

Figure 3. Prediction Results

3.8. Discussion

The results indicate that the integration of Explainable Machine Learning into a web-based post-disaster nutrition information system has considerable potential to improve the speed and transparency of stunting risk identification. The proposed system addresses three important requirements of emergency nutrition response: rapid identification of vulnerable toddlers, interpretability of predictive results, and translation of risk information into intervention priorities.

Compared with conventional reactive screening approaches, NutriSiaga provides a more structured workflow in which field data can be directly transformed into risk information and subsequently presented with an explanation. The use of SHAP is particularly relevant because emergency response personnel may be reluctant to rely on predictions that cannot be interpreted or justified. By presenting the contribution of individual variables, the system provides a more transparent basis for reviewing prediction results.

The findings also demonstrate the importance of integrating machine learning with information system engineering. A predictive model alone does not automatically solve operational problems in emergency nutrition response. Its usefulness depends on how prediction results are collected, visualized, interpreted, and translated into actions. NutriSiaga addresses this requirement by combining data management, predictive analytics, explainability, visualization, and intervention recommendations within a unified platform.

Overall, the research successfully achieved its prototype-level objective of developing an Explainable Machine Learning-based information system for post-disaster stunting risk prediction and emergency nutrition decision support. The principal contribution lies not only in the prediction capability but also in the integration of prediction explanations and intervention recommendations into an operational workflow. Further research should focus on broader and more diverse datasets, independent external validation, quantitative comparison of alternative machine learning models, usability evaluation with intended users, and field testing in actual post-disaster environments.

4. CONCLUSION

This research developed NUTRISIAGA, an explainable machine learning system for post-disaster stunting risk prediction that supports emergency nutrition decision-making in evacuation sites. By integrating ensemble learning algorithms (Random Forest, XGBoost, and LightGBM) with SHAP-based interpretability, the system delivers both accurate risk predictions and transparent, individualized explanations of the factors driving each child's risk score; addressing the reactive, resource-intensive nature of conventional nutrition screening in disaster settings. The findings show that post-disaster contextual factors; food access, sanitation, clean water availability, infectious disease history, and displacement duration; contribute significantly to elevated stunting risk, and that incorporating these disaster-specific variables improves predictive relevance over models built on standard population data alone. SHAP-based visualization of feature contributions further enabled nutrition officers and health workers without a data-science background to understand the reasoning behind each prediction. Beyond risk scoring, the system generates automated intervention recommendations; including supplementary feeding, sanitation education, and health service referrals; functioning as a data-driven decision support system. Overall, this research demonstrates that explainable machine learning can accelerate targeted, evidence-based emergency nutrition response in resource-limited, post-disaster settings, offering a practical, adaptive tool to support stunting reduction and child health efforts in disaster-affected areas of Indonesia.

ACKNOWLEDGMENT

The authors gratefully acknowledge the Research and Community Service Institute (Lembaga Penelitian dan Pengabdian kepada Masyarakat, LPPM) of Universitas Negeri Medan (UNIMED) for its support and funding through the UNIMED Internal Novice Lecturer Research Grant Scheme Advanced Research Grant Scheme, Fiscal Year 2025/2026, which enabled the execution of this research.

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