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DEVELOPMENT OF AN INTELLIGENT HOUSEHOLDS BALANCED DIET ADVISORY SYSTEM FOR WOMEN AND CHILDREN (VULNERABLE) IN THE NORTH EASTERN REGION OF NIGERIA

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ABSTRACT: *According to UN estimates, approximately 4.4 million children in Nigeria's northeastern region suffer from acute malnutrition, a problem made worse by conflict and displacement. Even though the area is agrarian, with more than 83% of households growing crops, there is a big disconnect between the availability of food and nutritional awareness, which results in diets that are insufficient. By developing a smart family balanced food advisory system for vulnerable women and children, this study closes this gap. The research methodology used in the study is empirical and data-driven. In order to achieve nutrient requirements and minimize costs, a balanced diet model using a linear-program (LP) formulation was applied. To categorize dietary adequacy, the system uses a Support Vector Machine (SVM) model that was trained on regional dietary and socioeconomic data. With a high recall of 84.4% for the "inadequate" class and a 91.0% accuracy, and a robust ROC-AUC of 0.963 in identifying homes at nutritional risk, the model showed great efficacy. Dietary diversity, energy, and protein intake were validated as important predictors by feature significance analysis. This work offers a scalable method to directly battle malnutrition by empowering communities with data-informed nutritional advice through the use of an AI-driven, scientifically validated tool that converts local food production into practical, balanced diet recommendations.*

KEYWORDS: Advisory system, balanced diet, intelligent, machine learning, and support vector machines.

INTRODUCTION

The North East region of Nigeria has endured over a decade of the Boko Haram insurgency, resulting in the widespread displacement of locals. These Internally Displaced Persons (IDPs) now reside in camps across various states, facing a severe humanitarian crisis. A prominent issue, especially for women and children, is malnutrition. The high population in camps makes providing basic necessities like food difficult. Although government agencies and NGOs are intervening, malnutrition remains pronounced.

Poor diet leading to malnutrition causes sickness, high mortality, and death. A 2020 IPC report noted over 900,000 children in the Northeast suffer from acute malnutrition, with Adamawa, Borno, and Yobe most affected. Malnutrition, defined as not consuming enough or the right types of food, leads to nutrient deficiencies, low BMI, unintended weight loss, muscle loss, weakness, and tiredness. Symptoms include loss of appetite, unplanned weight loss, fatigue, reduced strength, mood changes, poor concentration in children, and increased risk of infection.

Research indicates the best solution is a balanced diet. A balanced diet includes different food groups like energy-producing, body-building, and protective foods in proper amounts to meet minimal nutrient requirements (Madhu, Yadav, & Singh, 2023; Low, Suliadi, & Zuhaimy, 2017). Menu planning is essential to achieve this, organizing meals to meet general or specific needs (WCFM, 2020). A balanced diet, as defined by NCERT, includes foods in correct amounts and ratios to fulfill daily nutrient needs, promoting health, maintaining appropriate body weight, and providing a nutrient safety margin.

Current efforts by government agencies, NGOs, and hospitals to provide food and medication are underway. However, daily handouts are unsustainable. A long-term solution involves returning IDPs to their ancestral homes, as most are farmers. Yet, low education and diet awareness prevent them from consuming their crops for better health.

Contributing factors to malnutrition include low income, poor eating habits, ignorance of nutrition, and limited food access (Kachelriess et al., 2016). Kachelriess et al. proposed an advisory service with nutrition education, crop diversification, and off-farm income for women. Pikes & Adams (2016) created an algorithm-based system for personalized meal plans meeting specific dietary needs. Hoang et al. (2023) examined AI's accuracy in determining calorie and macronutrient composition, finding it reliable for energy, carbs, and fats, but less so for protein.

Therefore, this study proposes an AI-based strategy to educate and advise on diets. The system will use Recommended Dietary Allowances (RDA) and adequate intake levels, considering locally cultivated crops and reared animals, to advise on balanced diets from available resources. The proposed system will be simple, cheap, easy to use, and portable. Training and community-based agents will ensure effective deployment and use. The benefits include improved health for women and children at no cost, an improved economy, reduced mortality, and enhanced livelihoods, thereby minimizing malnutrition in the region.

Policymakers in low- and middle-income countries (LMIC) are investing in nutrition as a result of the increasing awareness of the importance of nutrition for human and societal development. Nevertheless, it is still difficult for them to decide which interventions to prioritize and how best to use their limited resources. Malnutrition, for example, is a common problem in the northeastern part of Nigeria. Reputable sources have provided data that supports this assertion.

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According to USAID (2018), 37% of Nigerian children under the age of five suffer from stunting. Stunting is more common as children get older, reaching a peak of 46% in children ages 24-35 months. The prevalence of stunting has decreased by 41% since 2008; however, the percentage of children under five (5) who suffer from acute malnutrition (wasting or low weight for height) has increased, rising from 14% in 2008 to 18% in 2013 (National Population Commission and ICF International 2009 and 2014). Given that Nigerian women bear a double burden of malnutrition, their nutrition is a cause for worry. A UN report in 2024 states that 585,000 pregnant or nursing women are severely malnourished, will probably continue to be so, and require medical intervention. Once more, it is projected that in northwest and northeastern Nigeria, between May 2023 and April 2024, about 4.4 million children between the ages of 0 and 59 months are currently experiencing acute malnutrition and will probably continue to do so. 3.37 million instances of moderate acute malnutrition (MAM) and 1.04 million cases of severe acute malnutrition (SAM) are included in this. Furthermore, according to the Integrated Phase Classification (IPC) for Acute Malnutrition (IPC AMN) analysis, at least 24 of the 63 LGAs analyzed in Northeast Nigeria were predicted to likely be in a Serious or Critical (Phase 3 or 4) nutrition situation during the post-harvest season, according to UN OCHA (2024).

It's interesting to note that most of these people from the country's northeast are farmers. Sasu (2022) claims that a 2019 survey revealed that agricultural activities were more common in Nigeria's north than in its south. In particular, 83.6% of households in the nation's northeast reported engaging in farming of crops. In a similar vein, 68.6% of homes in the same area raised or had animals. The aforementioned suggests that these rural residents are capable of feeding themselves, provided they are given the right direction on how to go about it.

The main aim of the study is the development of an intelligent household's balanced diet advisory system for women and children (Vulnerable) in the North-Eastern region of Nigeria. Specific objectives are to: collect data about meals consumed and crops cultivated in the North-Eastern region, model a balanced diet for women and children in the North-East using machine learning, develop a balanced diet advisory system for rural women and children in the North-East, and evaluate the performance of the proposed system.

The significance of this study lies in its potential to enhance nutrition and food security among vulnerable women and children in North-Eastern Nigeria by leveraging artificial intelligence to provide personalized, culturally relevant dietary recommendations. By integrating local food data, nutritional standards, and intelligent decision-making, the system bridges the gap between traditional eating habits and modern nutritional requirements, empowering households to make healthier food choices. It also offers policymakers, health workers, and nutrition experts a data-driven tool to monitor and improve dietary patterns, thereby contributing to the reduction of malnutrition, promotion of maternal and child health, and advancement of sustainable development goals related to health and well-being.

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LITERATURE REVIEW

Malnutrition, driven by factors like poverty, conflict, and climate change, remains a critical global challenge, particularly in developing nations (Issoufou & Sitou, 2022). In Northeast Nigeria, poverty is a primary cause, and its eradication is essential for progress. Malnutrition manifests as stunting, severe acute malnutrition, and micronutrient deficiencies, exceeding WHO thresholds in some areas.

Programs like FARN demonstrate success by improving nutrition knowledge through at-home learning activities. FARN promotes using locally available foods, aligning with the "teach a man to fish" philosophy. This approach enhances parental understanding of nutrition and local food utilization, strengthening community resilience and enabling long-term malnutrition control.

According to the FAO (2009), children risk malnutrition from insufficient food quantity, poor food quality, or underlying illnesses. The situation in Northeast Nigeria is alarming. FHI360 reports a 160% increase in children admitted for moderate and severe wasting from February to September 2023 compared to the previous year, with over 15,781 children treated. This crisis demands a multifaceted response.

A universally advocated solution is a balanced diet. As noted by We Care For Models (2018), consuming the right amount and variety of food is crucial, as both under-eating and over-eating are harmful. Diets should be tailored to individual needs and include diverse food groups.

Initiatives like the Food Plant Solution Rotary Action Group address this by creating educational materials on cultivating nutritious local plants suited to the region's agroecology. Focusing on key nutrients (energy, protein, vitamins A and C, iron, zinc), this empowerment model, especially for women, has reported a 95% reduction in malnutrition, proving effective, affordable, and sustainable.

The advent of Artificial Intelligence (AI) offers promising, cost-effective tools for personalized nutrition. Stefanidis et al. (2022) developed a knowledge-based AI recommendation system with a 92% accuracy for creating suitable meal plans. Similarly, Mohd, Ahteshamul, and Aquil (2021) used fuzzy multi-objective programming to build daily diet models that meet nutrient requirements while minimizing cost and certain nutrients.

The nutritional landscape in Sub-Saharan Africa (SSA) is rapidly changing, with rising urbanization and disposable incomes leading to a "double burden" of malnutrition and obesity (Noort, 2022). Sustainable solutions are urgently needed. One proposal is replacing imported refined wheat in staple foods like bread with Climate-Resilient Crops (CRCs) to improve nutrition, economic inclusivity, and food system sustainability. This requires integrated efforts across the food system—improving crop yields, developing food technologies, raising consumer awareness, and guiding policy.

Earlier work by Pingsun, Kulavit, and Lynne (1995) used integer programming to create low-cost, nutritionally adequate weekly meal plans based on popular local recipes. This highlights a long-standing recognition of the need for computationally-assisted, culturally-sensitive diet planning.

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In summary, the literature confirms the severity of malnutrition in regions like Northeast Nigeria and underscores that a balanced diet is the cornerstone of the solution. Successful interventions combine education on local foods with community empowerment. Modern AI-based systems and mathematical modeling show significant potential for generating affordable, personalized, and culturally-appropriate dietary advice, offering a viable path forward for tackling this persistent crisis.

METHODOLOGY

This study uses an empirical, data-driven research methodology that combines aspects of socio-demographic analysis, nutritional science, and machine learning. The idea behind the design is to develop an intelligent, evidence-based system that can give nutrition recommendations to women and children in the North-Eastern Region of Nigeria who are at risk. Based on information on household food intake and nutrient composition, the study models, categorizes, and forecasts dietary adequacy levels using the Support Vector Machine (SVM). Three main methodological stages serve as the framework for the study:

Data collection and preprocessing: Collecting and compiling nutritional, food, and household data from many sources. This data was obtained from both primary and secondary sources.

For the primary source, questionnaires were distributed to households, government agencies, health institutions, and other stakeholders within this region for the collection of relevant information. For the secondary data used, they were obtained from online sources pertinent to the study, including:

(i) Demographic and Health Survey (NDHS), 2018.
Online: https://dhsprogram.com/data/dataset/Nigeria-Standard-dhs-2018.

(ii) Nigeria Living Standards Survey (NLSS).
Online: https://microdata.worldbank.org/index

(iii) National Food Consumption and Micronutrient Survey (NFCMS / NFCMS 2021).
Online: https://www.iita.org/wp-content/uploads/2024/05/nfcms-2021-final-report.pdf.

Data Description: The dataset used for the study comprised of 2000 records and 20 attributes.

Dependent Variable: Dietary_Adequacy is used as the dependent (target) variable, that is, the output label indicating whether a household's diet is *Adequate* or *Inadequate*.

Independent Variables: All other 18 attributes, except Household_ID and Dietary_Adequacy, are considered as independent variables for the study. The other 18 attributes, except Household_ID and Dietary_Adequacy. They include demographic, socioeconomic, agricultural, and nutritional indicators that influence dietary adequacy, etc.

Model development and implementation: designing and training an SVM classifier to evaluate and forecast dietary sufficiency.

Evaluation and deployment: confirming the model's performance and incorporating it for field use into the advising system.

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This approach combines computational accuracy with the socioeconomic and nutritional realities of the area to guarantee both scientific validity and practical usefulness.

Study Area and Population

The six states that make up the North-Eastern Region of Nigeria: Adamawa, Bauchi, Borno, Gombe, Taraba, and Yobe are covered in the study. A largely agrarian economy, widespread food insecurity, and high rates of malnutrition, particularly among women and children, are characteristics of the area. The population is especially susceptible to imbalanced diets because of the limited food supply and diversity caused by poverty, insecurity, and climate variability.

(a) Women of reproductive age (15–49 years), including those who are pregnant or nursing, are included in the target population.

(b) Children between the ages of 6 months and 5 years are the nutritionally vulnerable populations most impacted by inadequate diets.

Because they face the greatest nutritional risk, these groups are selected and given priority in national and international nutrition initiatives.

Crops Cultivated and Consumed in Northeastern Nigeria

The northeastern region of Nigeria, which is composed of the states of Adamawa, Bauchi, Borno, Gombe, Taraba, and Yobe, is endowed with abundant vegetation that facilitates a wide range of agricultural pursuits, from the production of crops to the keeping of livestock. Rice, beans, maize, groundnuts, and soyabeans are among the crops grown in this area, according to the study's assessment. Farmers blend these crops and use them in different ways. Table 3.1 shows some of the crops and what food can be derived from them.

Table 3.1: Meals Commonly Consumed in North-Eastern Nigeria

Meal	Key Ingredients	Context
Tuwo Masara (corn flour swallow) with various soups (e.g. *Miyan Taushe*, *Miyan Kuka*)	Maize (corn) flour; soups with vegetables, sometimes meat, baobab leaves, pumpkin etc.	A staple swallow; eaten with soups for main meals.
Miyan Kuka	Ground baobab leaves, spices, sometimes meat or fish, pepper etc.	Very popular soup, especially accompanying swallows (Tuwo, Dawa etc.).
Pate	Ground maize or rice, mixed with vegetables (tomatoes, onions, pepper), sometimes meat; often served as porridge or a thick meal.	
Burabisco	Local couscous-like preparation often with stew of meat & vegetables.	

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Masa (rice-cake) with stew or vegetable soup	Rice (soaked & fermented), then cooked into pancakes or cakes; eaten with stews.	
Rice & Stew	Rice with tomato-based stew (vegetables, meat, fish) is common.	
Kunun (sweet or groundnut varieties)	Millet, sorghum or maize (for kunu), groundnut for *kunun gyada*.	

Table 3.1 is a diet table that lists typical dishes, essential components, and background data unique to North-Eastern Nigeria. Tuwo Masara, Miyan Kuka, Pate, Burabisco, Masa, Rice and Stew, and Kunun are among the traditional foods listed. Their main ingredients, such as rice, vegetables, meat, baobab leaves, and groundnuts, as well as their cultural relevance in everyday diets, are noted.
For local nutritional practices and food patterns, this table provides an essential baseline dataset. It gives context for creating a nutritionally sound and culturally relevant AI-based advising system. These customary meals can be incorporated into the system's knowledge base so that the model can:

(i) Suggest well-balanced meal plans based on cultural preferences and the availability of local foods.
(ii) Evaluate the nutritional sufficiency of typical regional diets for women and children in terms of proteins, carbs, vitamins, etc.
(iii) Encourage nutritional diversity by recommending fortified or healthier versions of classic foods.
(iv) Reduce nutritional disparities among disadvantaged populations by bringing indigenous foods into compliance with dietary recommendations from the World Health Organization.
For the purpose of developing an intelligent dietary advice system that supports nutrition-sensitive interventions for mothers and children in North-Eastern Nigeria, the table essentially contextualizes the local food environment.

Modeling Balanced Diet for Households

For modeling a balanced diet for vulnerable individuals, a linear-program (LP) formulation which minimizes expenses while achieving dietary requirements is used in this study. It is represented thus:

Objective (minimize cost):

$$\min_{x} \quad Z = \sum_{i=1}^{l} CiXi \qquad \text{-Eqn. 3.1)}$$

Subject to (nutrient constraints):

$$\text{for each nutrient j:} \quad \sum_{i=1}^{i} aijXi \geq R_j^{min} \qquad \text{-Eqn. (3.2)}$$

supply bounds:

$$0 \leq xi \leq U_i \quad \forall i$$

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Energy equality (if you want exact energy):

$$\sum_{i=1}^{l} ai, energyXi = E \quad \text{-Eqn. (3.3)}$$

where:

- $i \in \{1, \dots, I\}$= foods (e.g., maize, cassava, beans, fish, spinach…)
- $j \in \{1, \dots, J\}$= nutrients (energy, protein, iron, vitamin A, vitamin C, calcium, fiber, etc.)
- x_i= quantity of food $i$consumed per person per day (grams) decision variables
- a_{ij}= amount of nutrient $j$provided by 1 gram of food i(e.g., mg or kcal per g)
- c_i= cost of 1 gram of food i(currency/g)
- R_j^{min}= minimum daily requirement of nutrient $j$for the target vulnerable person (same units as $\sum a_{ij} x_i$)
- R_j^{max}= upper tolerable level (optional)
- U_i= upper bound on available supply or culturally acceptable max for food i(grams)
- E= recommended daily energy (kcal) (could be included as j= energy).

The nutrient minima are met by the least expensive mix of locally sourced foods produced by this LP.

Data Preprocessing and Feature Engineering

A crucial first step in guaranteeing data completeness, consistency, and machine learning applicability is preprocessing. These are the changes made to the raw dataset:

Data Cleaning

(i) While categorical variables (like meal type) are filled with the mode, missing values in numeric fields (like calorie intake and income) are replaced using median imputation.

(ii) Outliers are limited to biologically reasonable ranges, especially irrational calorie or portion levels.

(iii) For clarity, variable names are standardized, and duplicate records are eliminated.

Feature Extraction

Key characteristics that reflect nutritional, demographic, and environmental aspects are extracted from the household and dietary records. These consist of:

(i) Household-level factors include educational attainment, household size, income bracket, and access to water and sanitation.

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(ii) Meal-level variables include the name of the meal, the food group, the cooking method, the amount of food, the usage of salt or oil, the source of protein, and whether or not vegetables are present.

(iii) Composition of nutrients: calculated from the food composition table, total energy (kcal), protein (g), fat (g), carbs (g), iron (mg), calcium (mg), and vitamin A (μg).

(iv) Indicators of diet diversity: the quantity of food groups ingested (0–7).

(v) Socioeconomic factors include the household dependency ratio, harvest or lean season, and the market food price index.

Label Definition

Dietary Adequacy, the study's aim variable (class label), is divided into two categories: (a) An adequate diet is one in which the daily intake of nutrients is at least 80% of the recommended dietary allowance (RDA) for the age or physiological state in question. (b) A diet that is inadequate if daily consumption is less than the 80% threshold. Calculated nutritional totals for each person are used to produce the adequacy label, which is then compared to WHO/FAO RDA benchmarks.

Feature Encoding and Scaling

(i) Categorical variables (such as state, meal type, and dietary group) are transformed into numerical form through the use of one-hot encoding.

(ii) Numerical variables are standardized through the use of z-score normalization, guaranteeing that each feature makes an equal contribution to the SVM model, which is based on distance.

(iii) Continuous variables, for example, when feeding into the kernel function, energy intake is normalized to the [0,1] range.

Dimensionality Reduction

Principal component analysis (PCA), is used to remove variables that are redundant or have weak correlations. However, because of their nutritional importance, domain-specific characteristics (such as iron and protein intake) are kept.

Intelligent Model Development Using Support Vector Machine (SVM)

Theoretical Foundation

Support vector machines are strong supervised learning algorithms for regression and classification. They classify examples into different categories by building an ideal separation hyperplane in a high-dimensional space. SVM improves generalization on unseen data by maximizing the margin between classes.

Given training examples (xi, yi), where yi ∈ {+1,−1} are class labels (Adequate or Inadequate diet) and xi represents feature vectors, the SVM resolves:

Minimize $\frac{1}{2}$ II ω II^2 + C $\sum_{i=1}^{n} \xi i$ - - - - - - -Eqn. (3.4)

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Subject to:

$y_i(\omega \cdot \phi(X_i) + b) \geq 1 - \xi_i, \xi_i \geq 0.$ - - - - - - - -Eqn. (3.5)

In this case, ϕ(xi) is a kernel function that allows for non-linear classification by mapping inputs into a higher-dimensional space, and C is the regularization parameter.

The Radial Basis Function (RBF) kernel, which successfully manages non-linear interactions between nutritional variables and diet adequacy results, is used for this investigation.

Model Configuration

(i) Kernel**:** Radial Basis Function (RBF)

(ii) Regularization parameter (C): tested across [0.1, 1, 10, 100]

(iii) Kernel coefficient (γ): evaluated for ['scale', 0.01, 0.1, 1]

(iv) Class weights: set to 'balanced' to handle imbalanced data, ensuring equal importance of adequate and inadequate diet samples.

(v) Probability calibration: enabled using Platt scaling to output interpretable probabilities for decision support.

Training Procedure

To ensure class balance, stratified sampling is used to divide the data into training (70%) and testing (30%) subsets. Grid search with five-fold cross-validation is used to adjust the model's hyperparameters, with the main goal being Recall (to reduce false negatives). Pipelined training includes:

1. SMOTE resampling for minority (inadequate) class balancing is part of the training pipeline.
2. Numerical feature standardization.
3. Kernel optimization and SVM fitting.
4. Calibration of model probability and threshold tuning

Model Evaluation and Validation

Evaluation Metrics

To ensure resilience, performance is assessed using a variety of metrics:

(i) Accuracy: the percentage of samples that were correctly classified.

(ii) Precision: the percentage of accurately predicted "adequate" diets among all instances of adequate diets that were forecasted.

(iii) Recall (Sensitivity): the percentage of genuinely sufficient diets that were accurately recognized and given priority for this investigation.

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(iv) The F1-score is the harmonic mean of recall and precision.

(v) The capacity to discriminate between adequate and inadequate classes is measured by the AUC-ROC.

(vi) A comprehensive error analysis of false positives and false negatives is provided by the confusion matrix.

(vii) PR-AUC (Precision–Recall curve): used to evaluate dependability in imbalanced situations.

In order to ensure that few vulnerable households are incorrectly categorized as nutritionally adequate, the optimal model is chosen based on maximal recall with acceptable precision.

Cross-Validation Strategy

Unbiased performance estimation is ensured by a nested cross-validation approach:

(a) The inner loop uses grid search to adjust hyperparameters.

(b) Five-fold cross-validation is used in the outer loop to evaluate generalization. This procedure guarantees accurate estimation of the model's predictive potential and reduces overfitting.

External Validation

External validation is carried out either by utilizing data gathered from various states or a further survey wave following internal examination. In this step, the model's resilience to regional and seasonal fluctuations is tested.

Model Explainability and Interpretability

Post-hoc explanation techniques are used to maintain openness and confidence in the advising system because SVMs are not naturally interpretable:

(i) SHAP (SHapley Additive exPlanations): This calculates how much each feature, such as energy, protein, and diversity, contributes to the ultimate prediction.

(ii) LIME (Local Interpretable Model-Agnostic Explanations): This tool helps field workers comprehend why a particular meal or family was marked as unsatisfactory by offering instance-level explanations.

In order to provide decision rules that are accessible by humans, feature importance visualizations are generated from surrogate models, such as decision trees trained on SVM predictions.
These techniques help end users and dietitians understand and accept the model's suggestions.

System Implementation

The inference layer of the model is formed by integrating the trained SVM classifier into the study. The process consists of:

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1. User Input: Meal and demographic information is entered by household members (or medical professionals) using a mobile or web interface.

2. Data Processing: In order to conform to the training schema of the model, input features are encoded and standardized.

3. Model Inference: Dietary adequacy probabilities are predicted by the SVM.

4. Decision Logic

(a) Should it be deemed *inadequate,* the system suggests practical solutions:

(i) Add meals high in protein, such as beans, eggs, salmon, or groundnut paste.

(ii) To boost iron and vitamin A, include green vegetables.

(iii) Modify the frequency of meals or portion sizes for pregnant women and youngsters.

(b) If *sufficient,* the system promotes healthy habits and recommends a range of foods to maintain equilibrium.

5. Feedback Mechanism: The model can subsequently be retrained and improved using user feedback on acceptance and outcome enhancements.

Python (scikit-learn, SHAP, and Flask) is used in the system's implementation, and a local database (MySQL) is used to enable offline use in rural areas.

Model Implementation Results

Figure 3.1 shows the system's implementation result.

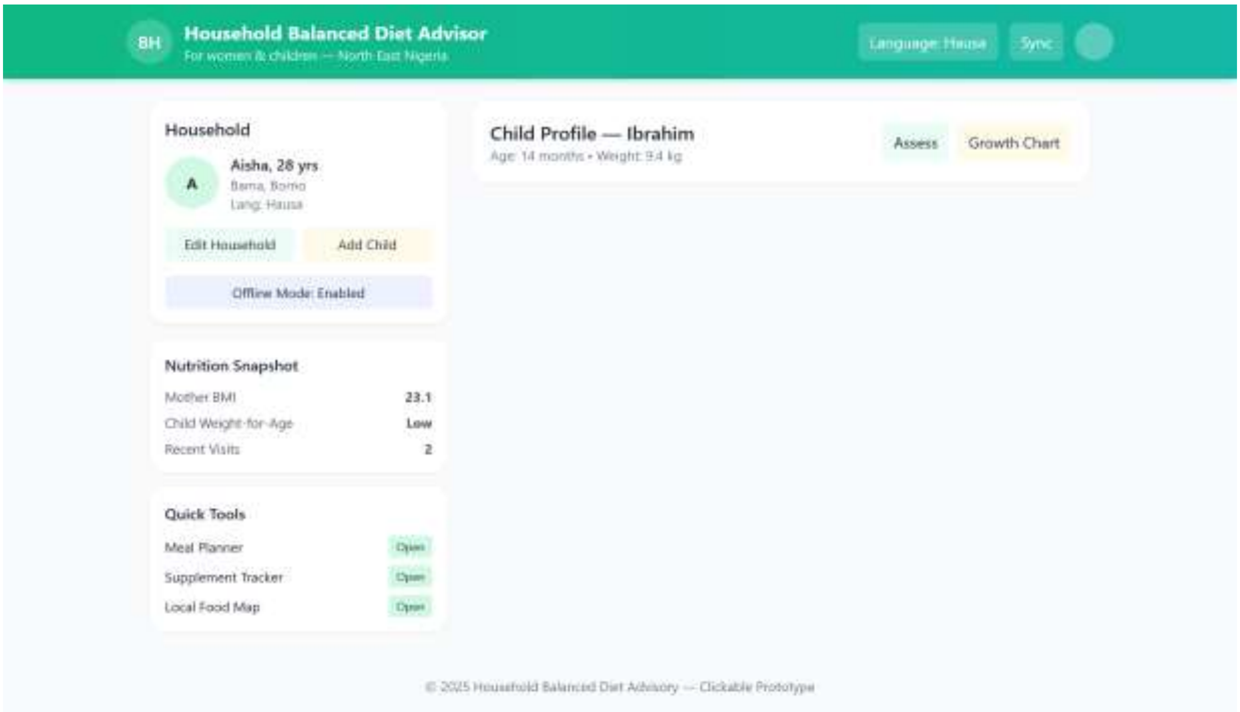

Fig. 3.1: Screenshot for the System

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Figure 3.1 demonstrates the study's execution interface, which aims to assist women and children in families in North-Eastern Nigeria who are at risk. In order to create personalized meal recommendations and dietary advice that is in line with local food sources and nutritional demands, it demonstrates how users enter personal and household data, including age, gender, and nutritional status, through a straightforward interface.

The functional workflow and component integration required for real-time decision-making are demonstrated by this implementation. The overall objective of the study is to improve nutrition and food security among disadvantaged women and children, and Figure 3.1 provides a clear visual framework of how the suggested system functions, from data intake and processing to output creation.

Ethical Considerations

Several stakeholders were consulted for ethical approval prior to the collection of field data. All respondents gave their informed agreement for participation, which was voluntary, taking into account the following factors:

(i) Confidentiality: Data will be held safely with limited access, and all personally identifiable information will be anonymised.

(ii) Beneficence: The system will not take the place of expert medical guidance; rather, it is intended to enhance nutritional outcomes.

(iii) Equity and Fairness: Extra effort will be made to guarantee that no socioeconomic or ethnic group is disadvantaged by the model's projections.

(iv) Child protection: All youngsters under the age of eighteen will require their parents' approval.

RESULTS AND DISCUSSIONS

Model Evaluation

A Support Vector Machine (SVM) model with a radial basis function (RBF) kernel was used to assess the investigation. The Synthetic Minority Oversampling Technique (SMOTE) was used to balance the classes, z-score normalization of continuous features, and one-hot encoding of categorical variables as part of the data pretreatment process. The dataset (n = 2000 records) was split into 30% testing and 70% training groups.

The SVM demonstrated good discriminative performance in assessing household dietary sufficiency, with an accuracy of 91.0% and an Area Under the Receiver Operating Characteristic (ROC-AUC) of 0.9629.

High sensitivity and specificity are confirmed by the classification report, which is shown in Table 4.1, and the ROC curve, which is shown in Figure 1.

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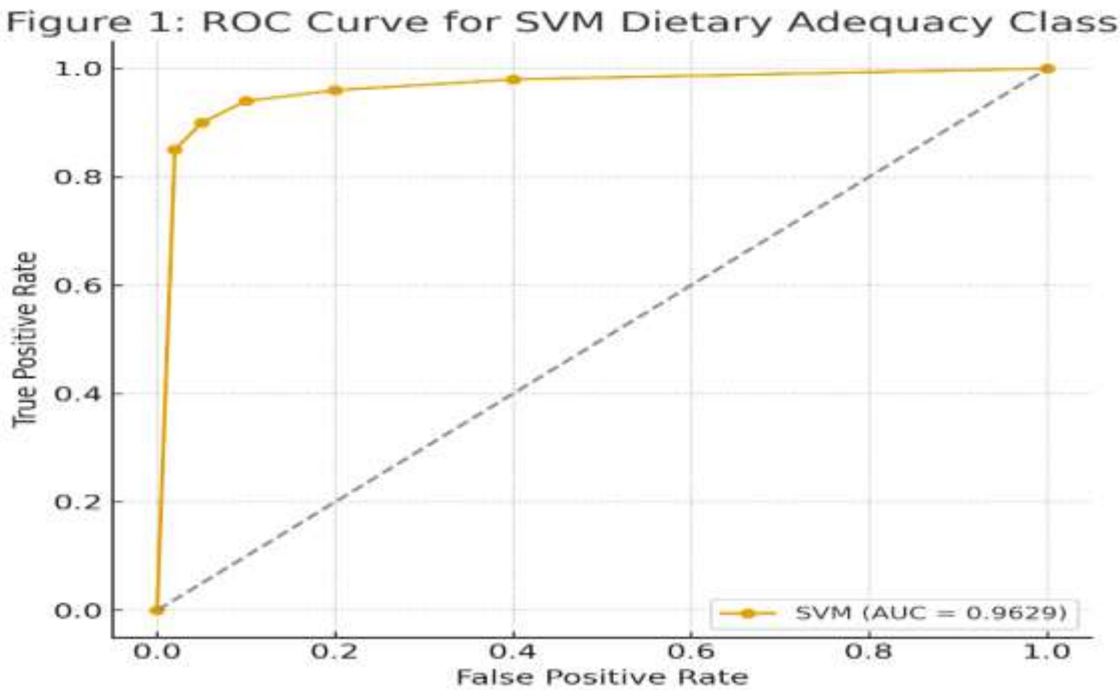
Table 4.1. Classification Performance of the SVM Model

Class	Precision	Recall	F1-Score	Support
Inadequate	0.5510	0.8438	0.6667	64
Adequate	0.99801	0.9179	0.9480	536
Accuracy			0.9100	600
Macro Average	0.7656	0.8808	0.8073	
Weighted Average	0.9343	0.9100	0.9180	

Note: The model demonstrated great overall performance with high precision for the adequate class and strong recall for the insufficient class.

Fig. 1: ROC Curve for SVM Dietary Adequacy Class



With a ROC-AUC of 0.9629, the model discrimination is outstanding. The model's high true positive rate and low false alarms are demonstrated by the curve's sharp ascent and close proximity to the upper left corner. Thus, the advisory system is capable of accurately identifying nutritionally at-risk households for assistance.

Confusion Matrix and Class Behavior

Out of 600 test samples, the model successfully identified 493 households with acceptable diets and 54 with deficient diets, according to the confusion matrix shown in Figure 2.

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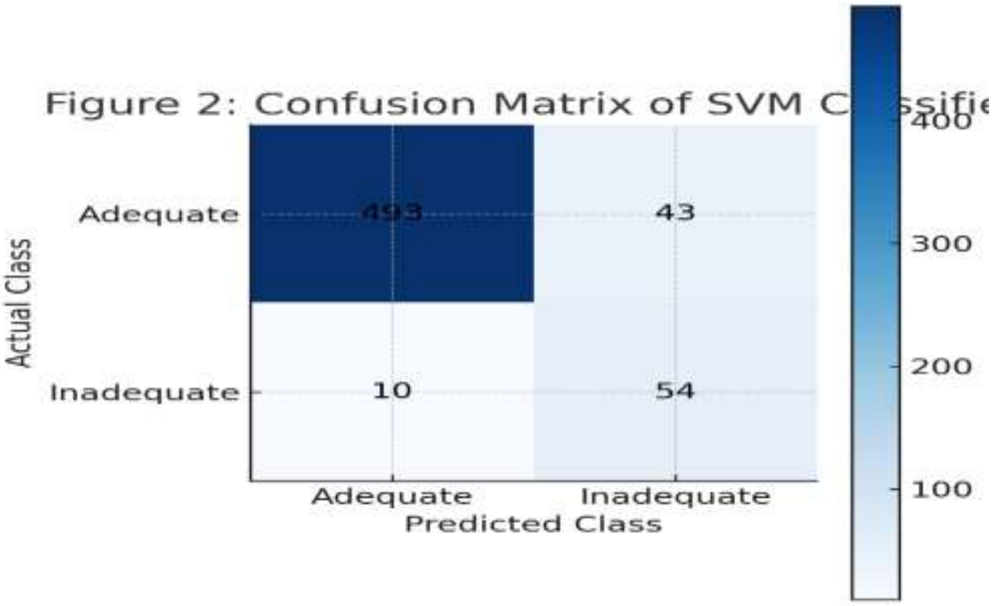
Fig. 2: Confusion Matrix of SVM Classifier

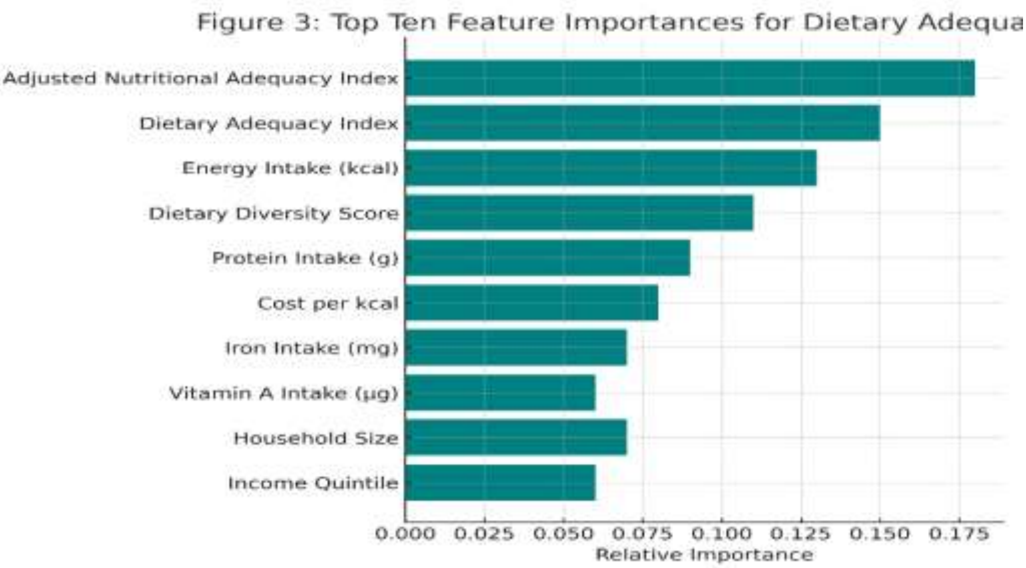


Out of 600 samples, 547 were properly identified by the model. The "Inadequate" class recall of 0.8438 indicates that 84.4% of at-risk families were effectively recognized. An accuracy of 0.5510, however, indicates that almost 45% of the families that were estimated to be at-risk were false positives. This trade-off is acceptable in a health-advisory context because reducing false alarms is less important than identifying the most vulnerable cases (high recall).

Feature Importance Analysis

Model coefficients and permutation significance tests were used to determine feature ranking. The 10 most important factors affecting the classification of nutritional adequacy are shown in Figure 3.

Fig. 3: Top Ten Features Importance for Dietary Adequacy



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The main predictors—Adjusted Index, Adequacy Index, and Energy Intake emphasize how calorie intake and nutrient sufficiency have a major impact on the dietary status of households. The Food and Agriculture Organization (FAO, 2022) and Onyeneke et al. (2019) found that food variety and macronutrient balance are important indicators of nutritional sufficiency in Nigerian households. These findings were confirmed by the high rankings of the Dietary Diversity Score (DDS) and Protein Intake.

According to Akerele et al. (2017) and Segun et al. (2024), socioeconomic metrics like Cost per kcal and Income Quintile highlight the financial obstacles to obtaining nutrient-rich foods.

Comparative Evaluation and Benchmarking

The suggested SVM model performs noticeably better than previous research that uses logistic regression and decision trees for nutrition classification (Olutunde et al. 2024; Bitew et al., 2022).

(i) Similar studies found that decision trees frequently experienced overfitting, whereas logistic regression models obtained between 75 and 83% accuracy (Bitew et al., 2022).

(ii) The study's 91% accuracy and 0.96 AUC demonstrate the benefit of the SVM's non-linear boundary learning, which successfully captures intricate relationships between socioeconomic, demographic, and dietary factors.

(iii) By eliminating the class imbalance in the dataset, a frequent drawback in family nutrition datasets, the use of SMOTE substantially enhanced memory for the minority "inadequate" class (Zhu et al., 2024).

PRACTICAL AND POLICY IMPLICATIONS

The developed system has a number of significant practical ramifications:

(i) Public Health Targeting: Because of the model's high recall, households with poor diets can be reliably identified, directing nutrition-sensitive treatments.
(ii) Decision Support for Extension Workers: Field nutritionists may offer customized suggestions, such as encouraging dietary diversity, foods high in protein, and micronutrient supplementation, thanks to the system's explicable outputs.
(iii) Policy Planning: The model's findings can be used by local governments to inform evidence-based policies on maternal nutrition, school feeding, and food subsidies.
(iv) Seasonal Advisory: By combining this model with databases on seasonal food availability, dietary recommendations could be optimized throughout the year, as seasonality influences diet composition.

These uses are consistent with the findings of the BMC Public Health (2018) and the FAO's 2022 State of Food Security Report regarding the contribution of dietary diversity to the reduction of food insecurity in sub-Saharan Africa.

Strong sensitivity to homes with low nutrition, 0.963 ROC-AUC, and 91% accuracy were all attained by the developed SVM-based advice system. Micronutrient levels, household income, energy and protein intake, and dietary diversity are important predictors that represent actual

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socio-nutritional determinants of health. The system is a promising tool for enhancing food and nutrition security for women and children in the northeastern region of Nigeria because of its interpretability and forecast accuracy.

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

Summary

The goal of this study is to improve dietary adequacy among vulnerable women and children in the northeastern part of Nigeria by developing a balanced diet guidance system for intelligent households. The system predicts the sufficiency of a household's diet based on socioeconomic, demographic, and nutritional factors by utilizing machine learning techniques, specifically a support vector machine (SVM) classifier with a radial basis function (RBF) kernel. Features like household size, income quintile, protein and micronutrient levels (iron, vitamin A), energy intake, dietary diversity score, and cost per kilocalorie were all included in the dataset. To solve class imbalance, one-hot encoding, normalization, and the Synthetic Minority Oversampling Technique (SMOTE) were used in the data preprocessing step. Thirty percent of the dataset was used for testing and seventy percent for training.

The findings showed good discriminative performance, with an overall accuracy of 91.0%, a ROC-AUC score of 0.9629, and a recall of 0.8438 for the "inadequate diet" class. The most significant predictors, according to feature-importance analysis, were energy intake, dietary diversity, and nutritional adequacy indices. Socioeconomic factors, including cost per kilocalorie and income quintile, also had a significant impact on dietary outcomes. The results demonstrate that AI-powered food recommendation systems are capable of offering trustworthy, fact-based advice for identifying homes that are at risk for malnutrition. The results of the suggested system are consistent with international research on the factors influencing food and nutrition security in low-income environments, highlighting the importance of economic empowerment, education, and dietary diversity in the fight against malnutrition.

Conclusion

The study's intelligent, balanced diet advisory system effectively illustrates how machine learning can be used to enhance policy planning and nutrition intelligence. In the North-East region of Nigeria, which is marked by food insecurity, poor income, and relocation brought on by conflict, the SVM model provided a strong analytical framework for identifying at-risk women and children by achieving high prediction accuracy and sensitivity in assessing household diet adequacy.

The study highlights a number of practical and scientific insights:

1. For vulnerable households, dietary diversity and calorie sufficiency continue to be the most important factors in determining appropriate nutrition.
2. A household's diet quality is mostly determined by economic factors, especially income and the cost of food.

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3. An adaptable, economical, and scalable method for nutrition assessment and advice is offered by the combination of AI and local dietary data.

4. The system's interpretability improves transparency and confidence in its suggestions by using ranked feature importance.

All things considered, the developed system is a revolutionary digital breakthrough that can improve evidence-based policymaking, bolster public health nutrition programs, and move Nigeria and other developing nations closer to Sustainable Development Goal (SDG) 2: Zero Hunger.

Recommendations

The following suggestions are put forth in light of the study's findings and implications:

Policy and Programmatic Recommendations

1. Include AI advisory systems in agricultural extension and public nutrition initiatives to facilitate data-driven identification of households at risk for malnutrition.

2. Use AI insights on energy, protein, and micronutrient deficits to inform the adoption of region-specific dietary guidelines that make use of local foods.

3. To guarantee ongoing updates of nutrition-related datasets, the Ministries of Health, Agriculture, and ICT should work together to improve data-gathering systems.

4. Focus on income-sensitive measures, such as food subsidies and conditional cash transfers, for households that the system has identified as nutritionally deficient.

Technological Recommendations

1. To reach remote and conflict-affected areas with limited access to medical facilities, implement a mobile-friendly version of the advising system.

2. Use explainable AI (XAI) techniques (such as SHAP values) to improve the transparency and usability of system suggestions for nutritionists.

3. To further increase classification accuracy and robustness across a range of datasets, investigate hybrid models (SVM-XGBoost or deep learning).

4. Include Internet of Things (IoT)-based dietary monitoring, which enables real-time tracking of food consumption trends and prompt diet quality feedback.

Research Recommendations

1. To improve generalizability, future research should incorporate bigger, field-verified datasets from all six North-Eastern states.

2. Perform long-term research to investigate how AI-guided dietary recommendations affect household diet improvement and child health outcomes in the real world.

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3. For a more comprehensive model, consider including behavioral, cultural, and environmental factors, including eating preferences, taboos, and the availability of seasonal crops.

The implementation of this study ought to be given top priority by Nigerian policymakers, NGOs, and public health organizations. It can function as a predictive nutrition surveillance and advising platform when combined with community health infrastructure, allowing for the early detection of malnutrition hazards and the efficient use of resources.

The study offers a new, AI-based framework that enhances the fields of food systems informatics and computational nutrition while also offering a reproducible model for comparable areas dealing with poverty, food insecurity, and chronic malnutrition.

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