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RESEARCH ARTICLE

GROWTH-SUPPORTING FOOD CONSUMPTION IN 6-23 MONTHS CHILDREN IN NORTHERN BENIN AND MINIMUM DIET DIVERSITY PREDICTION WITH SUPERVISED MACHINE LEARNING APPROACHES

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Abstract

Inadequate complementary feeding remains a major driver of child undernutrition in sub-Saharan Africa. Yet, the diet quality of infants and young children in northern Benin is poorly documented. This study monitored growth-supporting food consumption among children aged 6–23 months in the commune of Banikoara and assessed supervised machine learning (ML) approaches for predicting failure to achieve Minimum Dietary Diversity (MDD). A descriptive longitudinal study was conducted from November 2023 to July 2024 in five districts.Data were collected over five rounds using a non-quantitative 24-hour recall based on the infant and young child feeding diet quality questionnaire applied to 149 children. Multivariate Generalized Estimating Equations identified determinants of MDD, Egg and Flesh Food (EFF) and Fruit and Vegetable (FV) consumption.Meanwhile, seven supervised ML algorithmspredictedJulyMDDoutcomeusingsocioculturalgroup,livingdi strictandprevious MDD outcomes as predictors. MDD prevalence declined over time and reached its lowest level in July 2024 whereas EFF and FV consumption increased. Living in Soroko and Somperekou districts favored MDD where as Gourmantche children were disadvanta ged. Logistic regression achieved the highest discrimination performan ce (AUC = 0.65), while Decision Tree achieved the highest F1-score (0.70).

Although predictive performance remained modest, the models demonstrated the feasibility of identifying children at risk of failing to achieve MDD during the critical month of July using routinely collected information. This may support targeted nutrition counselling and early intervention among nutritionally vulnerable children in northern Benin.

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Introduction:-

Dietis deeply linked tonutritional status. A balanced diet contributes to an optimal nutritional status. Infant malnutrition could be tackled by improving infant diet quality.Diet quality (DQ) is evaluated through its macronutrient balance, essential nutrientcontent to cover needs and diversity (Raru et al., 2023; Shang et al., 2020).DQ could be evaluated with (a) Acceptable Macronutrients Distribution Ranges (AMDRs) which measuresthe proportion of total energy derived from carbohydrates, proteins and fats, (b) Healthy Diet Score (HDS)which measures the consumption of healthy food groupsand (c)Diet Diversity Score (DDS) which is the count of food groups consumed(Raru et al., 2023; Van et al., 2022; Shang et al., 2020).

DDS remains a good proxy measurement to evaluate the nutrients intake adequacy in a study population (Diop et al., 2025). It is useful for assessing intake of micronutrient-dense foods(e.g. (1) legume and fruit and (2) egg and flesh foods) (del Valle M et al., 2024; Kennedy, 2009). A total of eight food groups (i.e. cereals/roots/tubers, legumes/nuts, dairy products, flesh foods (meat/fish/poultry), eggs, vitamin-A-rich fruits, other fruits, and vitamin-A-rich vegetables) are consideredto evaluate the DDS of children(Setegn & Dejene, 2025). Minimum Dietary Diversity (MDD) is achieved when a child consumes at least 5 of these eight food groups within a 24-hour period (Raru et al., 2023). As diet quality index, MDD is anInfant and Young Child Feeding (IYCF) key indicatorsfor evaluatingfood intake in low-income regions (Raru et al., 2023; Setegn & Dejene, 2025).In sub-Saharan Africa, the prevalence of MDD among children aged 6-23 months rangesfrom 5.6% (Burkina Faso) to 43.9% (South Africa)(Raru et al., 2023). Most factors affecting MDD are food environment, household wealth,geographic context,maternal education and access to healthcare (Ebido et al., 2025; Hailu et al., 2025).

Moreover, recent indicators such as Egg and Flesh Food (EFF) consumption and Zero Vegetable or Fruit (ZVF) intake have been introduced to monitor the consumption of critical growth-supporting foods (Hailu et al., 2022). Only 30% of children (6-23 months) consumed egg and flesh foods in Benin (Zemene et al., 2024). Children protein intake is mainly provided by legumes. Essential micronutrients (Iron, Zinc, VitaminA) as well as essential fatty acids and high-quality proteins are provided by EFF (Hailu et al., 2022).

FV intake remains low in Benin although there is a variety of leafy vegetable (African eggplant, amaranth, Vernonia leaves, cowpea leaves and cassava leaves, baobab leaves and kenaf leaves) and fruits (e.g. tomato and okra fruit) are grown locally and value in infant nutrition(Mitchodigni-Houndoloa et al., 2024; Koukou et al., 2022; Honfo et al., 2010). FV consumption is limited by (a) accessibility and affordability, (b) seasonality and environmental constraints and (c) consumer food habits and food preferences (Diatta et al., 2025; Mitchodigni-Houndolo et al., 2024). Essential micronutrients, beneficial phytochemical (carotenoids) and dietary fiber are amongthe benefits provided by FV (Mitchodigni-Houndolo et al., 2024; Hailu et al., 2022).

Machine Learning (ML) is a toolkit that helps tackle global challenges related to malnutrition (e.g. undernutrition, micronutrient deficiency, obesity and dietary diversity and food intake) (Setegn & Dejene, 2025; Qasrawi et al., 2024; Ndagijimana et al., 2023; Bitew et al., 2022; Khan et al., 2019). Compared to traditional statistical models (e.g. Logistic regression), ML demonstrates higher prediction accuracy allowing (1) prioritization of risk factors (2) earlier identification of subjects at risk and (3) conception and execution of earlier interventions (Qasrawi et al., 2024; Bitew et al., 2022; Fenta et al., 2021; Khan et al., 2019).

ML modelsare usually evaluated based on their (1) discriminating power (area under the receiver operating characteristic curve), (2) overall classification (or prediction) accuracy and (3) ability to misclassify (sensitivity and specificity) (Ndagijimana et al., 2023; Van et al., 2022; Fenta et al., 2021). Random forest, Gradient Boosting, Logistic Regression, Support Vector Machine (SVM), K-Nearest Neighbors (kNN) and Decision Tree are the most popular ML techniques used on nutrition data (Qasrawi et al., 2024; Fenta et al., 2021; Khan et al., 2019).

The integration of modelling techniques (i.e. supervised ML) with the assessment of diet quality is a growing field in public health, used to predict nutritional risks, identify leading dietary determinants of disease, and guide policy interventions (Bitew et al., 2022). Unfortunately, its use in African countries (e.g. Benin) is still new and should be encouraged. Therefore, this study aims to (a) monitor changes in diet quality indicators among children aged 6-23 months in northern Benin and (b) identify the month associated with deterioration in dietary diversity.Specifically,EFF, FV and MDD were assessed over five survey rounds. In addition, supervised machine learning models were used to predict MDD status of the month associated with the deterioration of thedietary diversity. This combined approach provides both population level insights into longitudinal changes in dietary quality and individual level prediction of children at risk of failing MDD during the critical period.

Materials and Methods:-

A descriptive longitudinal study was conducted from November 2023 to July 2024 in the commune of Banikoara in northern Benin (Figure 1). The objective was tomonitor the diet quality of children aged 6 to 23 months. The target population was households with at least one child aged from 6 to 13 months at the time of the first round of the surveyin November 2023.Children were enrolled between 6 and 13 months of age and were followed longitudinally as they aged through the 6–23-monthIYCF period.The criteria for household inclusion were as follows: (1) residing inthecommune of Banikoara during the study period, (2) having at least one child aged from 6 to 13 months at the beginning of the study, (3) giving informed consent to participate in the study.

The criteria for household exclusion were as follows: (1) residing outside the commune of Banikoara, (2) having children whose age was outside 6 to 13 months at enrolment, (3) children whose parents did not give informed consent to participate in the study, (4) children whose parents did not participate in all the interviews planned for the study and (5) children with medical conditions that may influence their eating habits the day before the interview.
The districts included in thestudy were Banikoara, Founougo, Kokiborou, Somperekou and Soroko (Figure 1).In each district, simple random sampling was used to select the houses for the door-to-door visits.Households eligible in the visited houses were selected and interviewed. When no household was eligible in the selected house, the next eligible house on the right was selected as substitute.

A nonquantitative 24 h recall using a list-based questionnairewasused to collect data on the complementary feeding practices of children aged 6 to 23 months. The list-based questionscollected information on the 29 food groups according to the IYCF Diet Quality Questionnaire (DQQ) (Herforth et al., 2024). The country-adapted IYCF DQQ for Benin was downloadedfromGlobal Diet Quality Project(https://www.dietquality.org/countries/ben). Additional data on the socio-cultural group, marital status of the householdhead, living district andgender of the children were collected only in the first round of the survey since they remained unchanged during the study. Data were collected in the last week of November 2023, January 2024, March 2024, May 2024 and July 2024. The main local language spoken during the survey was Baatonou.A total of 153 children aged from 6 to 13 months were randomly chosen in the five districts of the commune of Banikoara and 4 children were excluded based on the criteria for household exclusion. Data of 149 children were processed and used for data analysis.

Ethical consideration:-

The ethical clearance was obtained from the Ethics Committee of the University of Parakou. The children's parents were informed about the conduct of the study, the objectives of the study, and the data collection procedures. Participation was voluntary, and participants could withdraw at any time without penalty. Verbal consent was obtained, followed by written informed consent. No financial incentive was offered for participation in this study.

Data analysis:-

Data were compiled andprocessed in Excel according to the instructions provided by WHO & UNICEF (2021). Monitored indicators were (1) Egg and Flesh Food (EFF) consumption and (2) Fruit and Vegetable (FV) consumption and (3) Minimum Dietary Diversity (MDD). MDD was defined as the consumption of at least five groups of food out of the eight defined food groups (i.e. breast milk, starchy based food, pulses, dairy products, flesh foods, eggs, vitamin A rich fruits and vegetables, others fruit and vegetables) during the 24 h recall.EFF, FV and MDD were defined as binary dietary diversity indicators and were analyzed with generalized estimating equations (GEE) using a binomial family with logit link function and an autoregressive AR(1) working correlation structure. For each binary indicator, a single multivariate GEE logistic model was fitted including all the predictors (i.e.children gender, living district, socio-cultural group, marital status of head of household and time point). Regression coefficients (β) and odds ratio (OR) with 95% confidence intervals (CI) and two-sided p-values were reported. Statistical significance was set at 5%. Reference categories were Female, Bariba, Banikoara, Monogamous for (a) children gender, (b) socio-cultural group, (c) living districtand (d) marital status of head of household, respectively. GEE analysis was performed in R 4.6.1 with the package geepack.

Classification training and prediction of MDD was performed using the software Orange Data Mining 3.39.Only data from participants who completed all five rounds of the study were used. The machine learning approach was intended to identify children at risk of failing to achieve MDD in July 2024 using socio-cultural groups, living district and previous MDD outcomes as predictors. No separate feature selection procedure was applied. The predictors were selected on the basis of the determinants identified by the GEE analysis. Socio-cultural groups and living districts were encoded as categorical. In addition, MDD status in November, January, March and May was encoded as binary predictor variables. MDD status in July was encoded as binary outcome class. Since all predictors were categorical or binary variables, no standardization or normalization was considered necessary for distance-based and margin-based models.To prevent information leakage from repeated measurements on the same subject, data were split at subject levelinto training (70%) and test (30%) sets. Data of 105 children (57 female and 48 male) were used to train the models. The data of the remaining 44 children (20 female and 24 male) were used to predict the MDD outcome.A 10-fold cross validation was used on the training set to train the models. The cross validation was stratified and repeated within the 10-fold framework. The class distribution of the outcome (MDD in July) was 59%versus 41% for MDD=0 and MDD=1, respectively. No sampling technique or any procedure was applied to modify the class distribution. Sixcategories of classificationmodels were tested on the data. Tree-based model (i.e. Decision Treeand Extreme Gradient Boosting), distance-based model (K-Nearest Neighbors), margin-basedmodel (Support Vector Machine), probabilistic classifier (Naive Bayes),linear model (Logistic Regression) and deep learning model (Artificial Neural Network) were tested. Hyperparameters selected for each model in Orange Data Mining 3.39 were presented in Table 1. The models were evaluated based on the precision, sensitivity (or recall), F1- score, specificity, accuracyand Area Under the ROC Curve (AUC).

Precision is the percentage of the Positive Samples Accurately Identified (PSAI) by the model out of the Predicted Positive Samples (PPS). High precision means good ability to predictpositive samplesaccurately.

$$\text{Precision} = \frac{\text{PSAI}}{\text{PPS}} \times 100$$

Sensitivity (or recall) is the percentage of Positive Samples AccuratelyIdentified (PSAI) by the model out of the Total Positive Samples (TPS). High sensitivity means low chance to misclassify positive samples.

$$\text{Sensitivity} = \frac{\text{PSAI}}{\text{TPS}} \times 100$$

F1-score is meant for minimizing misclassified negative samples whilemaximizing Positive Samples Accurately Identified (PSAI). High F1-score (F1-score >0.7) means good performance and good balance between precision and sensitivity.

$$\text{F1} - \text{score} = \frac{2 \times \text{precision} \times \text{sensitivity}}{\text{precision } + \text{sensitivity}} \times 100$$

Specificity is the percentage of Negative Samples Accurately Identified (NSAI) by the model out of the Total Negative Samples (TNS). High specificity means low chance to misclassify negative samples.

$$\text{Specificity} = \frac{\text{NSAI}}{\text{TNS}} \times 100$$

Accuracy is the percentage of samples correctly identified by the models out of the total samples.

$$\text{Accuracy} = \frac{\text{PSAI} + \text{NSAI}}{\text{Totalsamples}} \times 100$$

AUC compares overall performance of models. The overall performance of a model was evaluated as false, poor, moderate, high, and very high for (a)$0.5< \text{AUC} \leq 0.6$, (b) $0.6< \text{AUC} \leq 0.7$, (c)$0.7< \text{AUC} \leq 0.8$, (d) $0.8< \text{AUC} \leq 0.9$, (e) $0.9<\text{AUC}\leq 1$, respectively(Kannan & Menaga, 2022; Thamrin et al., 2021).

Results:-

Table 2 presents the characteristics of the study population. Of the 149 children selected for the study, 77 (51.7%) were female, while 72 (48.3%) were male. Children from the Bariba socio-cultural group represented 83.9% (n = 125) of the sample, followed by Gando (8.7%, n = 13), Gourmantche (4.7%, n = 7), and Zerma (2.7%, n = 4). According to living district, the largest proportions of children were enrolled in Somperekou (34.9%, n = 52) and Kokiborou (32.2%, n = 48). In contrast, Soroko contributed only 6.7% (n = 10). Half of the households (50.3%, n = 75) were monogamous. In addition, polygamous households came in second place with 35.6% (n = 53). Finally, the remaining households, defined by no marital status, represented 14.1% (n = 21). Table 3 presents the determinants of EFF according to children gender, socio-cultural group, living district, marital status of head of householdand the month. EFF consumption did not differ between male and female children. However, compared to children from Bariba socio-cultural group, EFF consumption was lower among Gourmantche children (OR = 0.28; 95 % CI: 0.14 -

0.57; p = 0.00) and Zerma children (OR = 0.33; 95 % CI: 0.19 - 0.59; p = 0.00). Meanwhile, no difference was observed for Gando children. Furthermore, using Banikoara as the reference living district, EFF consumption was lower and higher in Founougo (OR = 0.38; 95 % CI: 0.24 - 0.59; p = 0.00) and Soroko (OR = 2.11; 95 % CI: 1.17 - 3.80; p = 0.01), respectively. In contrast, EFF consumption in Kokiborou and Somperekou remained similar to Banikoara. Moreover, children from polygamous households were less likely to consume EFF than those from monogamous households (OR = 0.73; 95 % CI 0.53–0.99; p = 0.04). Compared to November 2023,the consumption of EFF remained similar in January 2024 while it was higher from March to July 2024 with a peak in May 2024 (OR = 3.51; 95 % CI 2.18–5.68; p =0.00).EFF consumption could be sequenced in three parts. EFF consumption was (1) low in November and January, then (2) higher in March and May, and finally (3) declining in July.

Table 4 presents the determinants of FV according to children gender, socio-cultural group, living district, marital status of head of householdand the month. FV consumption did not differ between male and female children. Furthermore, using Banikoara as thereference living district, FV consumption increased in Somperekou (OR = 14.09; 95% CI 3.20 - 62.01; p = 0.00) and Soroko (OR = 5.16×10^{10}; 95% CI1.43×10^{10} -1.86×10^{11};p = 0.00). Meanwhile, FV consumption remained similar inFounougo andKokiborou compared with Banikoara. Likewise, FV consumption remained similar (a) between the socio-cultural groups and (b) in all the households regardless of the marital status of the household head. Compared to November 2023, the consumption of FV kept increasing from January to July 2024.

Table 5 presents the determinants of MDD according to children gender, socio-cultural group, living district, marital status of head of householdand the month. MDD prevalence was similar between male and female children. However, compared to children from Bariba socio-cultural group, MDD prevalence was lower in Gourmantche children (OR = 0.44; 95 % CI 0.21 - 0.92; p = 0.03). Meanwhile, no significant differences were observed for Gando and Zerma children. Furthermore, using Banikoara as thereference living district, MDD prevalence was similar in Founougo and Kokiborou. In contrast, MDD prevalence was higher in Somperekou (OR = 2.99; 95 % CI 1.47 - 6.09; p = 0.00) and Soroko (OR = 7.90; 95 % CI 2.37- 26.36; p = 0.00). Moreover, MDD prevalence remained similar in all households independently of the marital status of the household head. Regarding the month, MDD prevalence remained high from January to May 2024 when compared to November 2023 with a prevalence peak in March 2024 (OR=5.90; 95 % CI2.98- 11.68; p=0.00). MDD prevalencedeclined in July 2024 (OR = 0.48; 95 % CI 0.30 - 0.79; p = 0.00). Accordingly, the MDD prediction was performed usingsocio-cultural group, living district and previous MDD outcomes.

Table 6 presents the predictive performance metrics of models developed to classify children according to their MDD status in July 2024.Unlike the GEE analyses reported in Tables 3-5, which estimate the association between explanatory variables and dietary outcomes, the objective of these models was to identify children at risk of failing to achieve MDD in July rather than to infer associations. Because the outcome classes were moderately imbalanced, model comparison focused primarily on AUC and F1-score.

Among the evaluated models, Logistic regression achieved the highest AUC (0.65). The second and third places were shared by Artificial Neural Network (AUC = 0.64) and SVM (AUC = 0.61), respectively. These values indicate poor discriminative ability. Regarding the F1-score, the highest values were observed for Decision Tree (0.70), SVM (0.69) and kNN (0.69). These F1-scoresindicate that models achieved a moderate balance between precision and sensitivity.

Although SVM achieved one of the highest F1-scores (0.69), its AUC remained low (0.61). This suggests that the modelachieved a reasonable balance between precision and sensitivity at the selected classification threshold. However, it had limited overall ability to discriminate children who did and did not achieve MDD in July. Nevertheless, the findings demonstrate the feasibility of using socio-cultural characteristics, living district and previous dietary diversity outcomes to identify children at risk of failing MDD during the critical month of July.

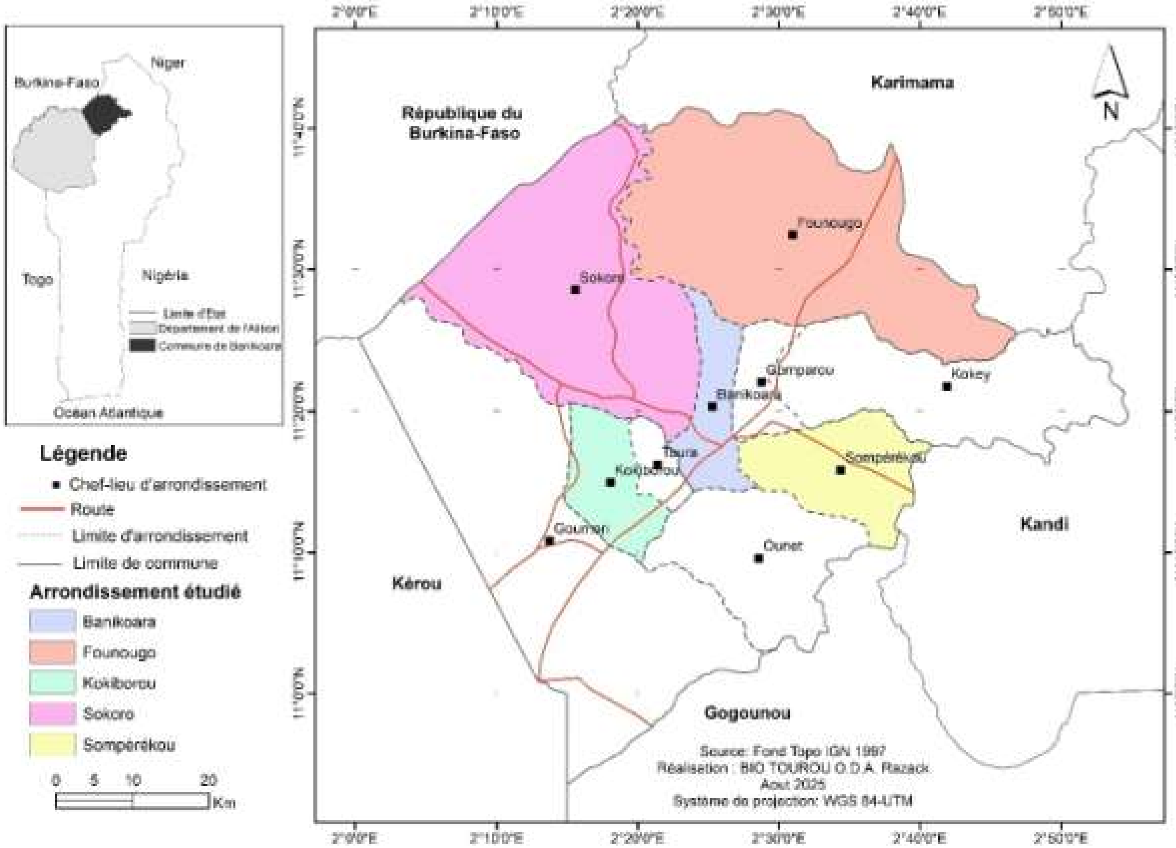

Figure 1: Study area and selected district of Banikoara.

Table 1: Models settings used in Orange Data Mining software for classification training and prediction

Classification model group	Models	Settings
Tree based models	Decision Tree	Minimum number of instances in leaves: 2 Do not split subsets smaller than 5 Limit the maximal tree depth to 100 Stop classification when majority reaches 95%
	Extreme Gradient Boosting	Number of trees: 100 Learning rate: 0.3 Growth control: limit depth of individual trees to 6
Distance based model	K-Nearest Neighbors	Number of neighbors: 5 Metric: Euclidean Weight: by distances
Margin based model	Support Vector Machine	Cost: 1.00 Regression loss epsilon: 0.10 Kernel: RBF Optimization parameters: Iteration limit (100)
Probabilistic classifier	Naive Bayes	-
Linear model	Logistic Regression	Regularization type: None
Deep learning model	Artificial Neural Network	Neurons in hidden layers: 100 Activation: Logistic Solver: Adam Regularization: 0.0001 Maximal number of iterations: 200

Table 2: Sample characteristics of the study population

Characteristics	Category	Sample size	Percentage
Gender	Female	77	51.7
	Male	72	48.3
Social cultural groups	Bariba	125	83.9
	Gando	13	8.7
	Gourmantche	7	4.7
	Zerma	4	2.7
Living district	Banikoara	20	13.4
	Founougo	19	12.8
	Kokiborou	48	32.2
	Somperekou	52	34.9
	Soroko	10	6.7
Marital status of the head of household	Monogamous	75	50.3
	Polygamous	53	35.6
	Others	21	14.1

Table 3: Multivariate GEE analysis of EFF fitted with children gender, socio-cultural group, living district, marital status of head of householdand month of data collection

Variables	β	OR	95% CI	p-value
Intercept	− 0.35	0.70	0.47 - 1.06	0.09
Gender				
Female	-	-	-	-
Male	0.27	1.30	0.99 - 1.71	0.06
Social cultural groups				
Bariba	-	-	-	-
Gando	− 0.19	0.82	0.51 - 1.33	0.43
Gourmantche	− 1.27	0.28	0.14 - 0.57	0.00
Zerma	− 1.10	0.33	0.19 - 0.59	0.00
Living district				
Banikoara	-	-	-	-
Founougo	− 0.98	0.38	0.24 - 0.59	0.00
Kokiborou	0.05	1.05	0.69 - 1.61	0.81
Somperekou	0.05	1.05	0.70 - 1.57	0.83
Soroko	0.74	2.11	1.17 - 3.80	0.01
Marital status				
Monogamous	-	-	-	-
Polygamous	− 0.32	0.73	0.53 - 0.99	0.04
Others	0.02	1.02	0.71 - 1.45	0.91
Months				
November 2023	-	-	-	-
January 2024	− 0.09	0.91	0.58 - 1.43	0.70
March 2024	1.07	2.91	1.80 - 4.71	0.00
May 2024	1.26	3.51	2.18 - 5.68	0.00
July 2024	0.72	2.04	1.23 - 3.39	0.01

GEE: Generalized estimating equations
EFF: Egg and flesh food

Table 4: Multivariate GEE analysis of FV fitted with children gender, socio-cultural group, living district, marital status of head of householdand month of data collection

Variables	β	OR	95% CI	p-value
Intercept	0.47	1.60	0.56 - 4.51	0.38
Gender				
Female	-	-	-	-
Male	− 0.28	0.76	0.43 - 1.33	0.34
Social cultural groups				
Bariba	-	-	-	-
Gando	− 0.46	0.63	0.25 - 1.58	0.33
Gourmantche	1.03	2.79	0.45 - 17.23	0.27
Zerma	− 2.35	0.10	0.01 - 1.28	0.08
Living district				
Banikoara	-	-	-	-
Founougo	− 0.89	0.41	0.15 - 1.11	0.08
Kokiborou	− 0.34	0.71	0.24 - 2.15	0.55
Somperekou	2.65	14.09	3.20 - 62.01	0.00
Soroko	24.68	5.16×10^{10}	1.43×10^{10} - 1.86×10^{11}	0.00
Marital status				
Monogamous	-	-	-	-
Polygamous	0.03	1.03	0.53 - 2.03	0.92
Others	0.52	1.69	0.68 - 4.19	0.26
Months				
November 2023	-	-	-	-
January 2024	2.20	9.07	3.60 - 22.84	0.00
March 2024	2.65	14.18	5.31 - 37.81	0.00
May 2024	3.39	29.53	8.27 - 105.48	0.00
July 2024	3.80	44.91	9.89 - 203.89	0.00

GEE: Generalized estimating equations
FV: Fruit and Vegetable

Table 5: Multivariate GEE analysis of MDD fitted with children gender, socio-cultural group, living district, marital status of head of householdand month of data collection

Variables	β	OR	95% CI	p-value
Intercept	− 0.32	0.73	0.35 – 1.53	0.41
Gender				
Female	-	-	-	-
Male	0.19	1.21	0.83–1.77	0.33
Social cultural groups				
Bariba	-	-	-	-
Gando	0.07	1.08	0.54–2.16	0.83
Gourmantche	− 0.81	0.44	0.21–0.92	0.03
Zerma	− 0.63	0.53	0.14–2.01	0.35
Living district				
Banikoara	-	-	-	-
Founougo	− 0.51	0.60	0.30–1.21	0.15
Kokiborou	0.24	1.27	0.61–2.66	0.52
Somperekou	1.10	2.99	1.47–6.09	0.00
Soroko	2.07	7.90	2.37–26.36	0.00
Marital status				
Monogamous	-	-	-	-
Polygamous	− 0.06	0.94	0.62–1.42	0.78
Others	0.64	1.89	0.97–3.67	0.06

Months				
November 2023	-	-	-	-
January 2024	1.44	4.20	2.61 –6.77	0.00
March 2024	1.78	5.90	2.98 –11.68	0.00
May 2024	1.20	3.31	1.90 –5.76	0.00
July 2024	− 0.73	0.48	0.30–0.79	0.00

GEE: Generalized estimating equations
MDD: Minimum Dietary Diversity

Table 6 Precision, sensitivity (or recall), F1- score, specificity, accuracy and Area Under the ROC Curve of models predicting thenon-achievement of MDD.

Model	AUC*	Accuracy	F1-score	Precision	Sensitivity (Recall)	Specificity
Logistic Regression	0.65	0.57	0.67	0.61	0.73	0.33
ANN	0.64	0.59	0.67	0.64	0.69	0.44
SVM	0.61	0.57	0.69	0.60	0.81	0.22
Naive Bayes	0.61	0.55	0.52	0.67	0.42	0.72
Extreme Gradient Boosting	0.60	0.57	0.66	0.62	0.69	0.39
Decision Tree	0.56	0.59	0.70	0.62	0.81	0.28
kNN	0.55	0.59	0.69	0.63	0.77	0.33

*AUC: Area Under the ROC Curve; ANN:Artificial Neural Network; kNN: K-Nearest Neighbors; SVM: Support Vector Machine

Discussion:-

This study provides evidence that diet quality among children aged 6–23 months in northern Benin varied according toliving district, socio-cultural groups, and time (months). In addition, it supports the prediction of non-achievement of MDD using supervised machine learning.Diet quality (especially FV, EFF and MDD) was consistently associated in this study with living districts over time and to a lesser extent to socio-cultural groups. Spatial inequality in the local food environment might be a major driver of complementary feeding quality in the study area. Food availability and dietary diversity could vary according to geographic patterns across West Africa. In addition to the disparity of MDD prevalence between West African countries (e.g. Côte d'Ivoire, Niger, Senegal), children in rural areas are more likely to fail MDD (Janmohamed et al., 2024). However, the disparity within rural areas had never been documented.This gap reflects unequal geographic access to diverse food sources and market systems within the same study area.In general food-system resilience is built on assets, diversification, education, and household support systems. Households with (a) bigger assets (land, livestock, income), (b) diverse activities (farming and other small businesses), (c) access to knowledge and (d) access to social safety nets (community-based support and access to credit from established institutions) demonstrate greater resilience during lean periods(Dereje et al., 2024; Myeki & Bahta, 2021).

Compared with Bariba children, Gourmantche and Zerma children were less likely to consume EFF whereas FV consumption did not vary significantly by socio-cultural group.Moreover, Gourmantche children are less likely to achieve MDD. It suggests that socio-cultural groups remained a determinant for evaluating the access to animal-source food.In many sub-Saharan African communities, livestock is primarily viewed as capital and social status rather than as animmediate food resource(Potts et al., 2019).Livestock could serveas food orbe retained for wealth and ritual purposes(Potts et al., 2019). To increase EFF consumption among Gourmantche and Zerma children, the perception and value of livestock should be explored first.Strategies to increase EFF consumption should be built on diversifying livestock to accommodatenutritional, social status and ritual purposes(Amadou & Saley Bana, 2018).

Children from polygamous households had lower odds of consuming EFF. Household structure could affect access to animal-source protein.Children of polygamous householdshad poorerlong-term nutritional outcomes thanfrom children of monogamoushouseholds(Owoo, 2018).Household-level food security might not ensure equitable access to EFF to all family membersof polygamous households.The month was among the predictors of diet quality. This reveals a marked seasonality in the study area. Seasonal variation in household dietary diversity with lower dietary diversity in the lean season has been documented in other African settings(Fentahun et al., 2018; Roba et al., 2019). From a programmatic perspective, July emerged as the critical month during which children are at greater risk of failing to achieve MDD. Monitoring and targeting the children at risk would be an efficient approach for food-based interventions.

The highest F1-scores were observed for Decision Tree (0.70), SVM (0.69) and kNN (0.69). These results indicate a moderate balance between correctly identifying children at risk of failing MDD and limiting classification errors. However, the relatively low AUC values suggest that the discriminative ability of the models remained limited.
Despite these limitations, the present findings demonstrate the feasibility of using routinely collected socio-cultural and dietary information to identify children at risk of failing to achieve MDD during the critical month of July. Early identification of these children could support preventive nutrition strategies. Indeed, community health workers could provide targeted counselling and follow-up before dietary diversity deteriorates. Although models are not sufficiently accurate to replace dietary assessments, they could serve as an initial screening tool to prioritize children for further nutritional evaluation and intervention.This approach therefore maximizesthe efficiency of limited nutrition services.

Study limitations:-

Several limitations should be considered when interpreting these findings. First, the study was conducted in a single commune in northern Beninand included only 149 children. This limits the generalizability of the results and the stability of the predictive models. Second, dietary data were based on non-quantitative 24-hour recalls. Therefore, day-to-day variation in food intake, portion size and nutrient intake were not captured. Third, the follow-up period covered only nine months and did not capture repeated annual cycles, which limits the ability to fully characterize seasonal variation in child feeding practices. Fourth, the machine learning models were evaluated only through internal stratified 10-fold cross validation. An independent external dataset is needed to confirm the stability, reproducibility and generalizability of the predictive models.These limitations suggest that the present findings should be interpreted as context-specific, while also pointing to important directions for future research.

Conclusion:-

This study provides the first longitudinal characterization of growth-supporting food consumption among children aged 6–23 months in Banikoara, northern Benin. It demonstrates that dietary adequacy is strongly patterned by geography and socio-cultural affiliation.Although consumption of EFF and FVincreased over the nine-month period, MDDprevalencedeclinedand reached its lowest level in July 2024.July was identified as a critical period for dietary vulnerability. In addition, the disadvantage observed among(a) Gourmantche and Zerma children and (b) children in polygamous households suggeststhat household food availabilitydoes not necessarily translate into equitable access to nutrient-dense foods. Interventions should therefore be adapted to local socio-cultural and household contexts.
Furthermore, supervised ML models demonstrated that children at risk of failing to achieve MDD in July can be identified using socio-cultural characteristics, living district and previous dietary outcomes. Although model discrimination remained limited, the moderate F1-scores indicate that routinely collected data contain useful predictive signals. Even if these models are not sufficiently accurate to replace dietary assessments, they could support the early identification of nutritionally vulnerable children.

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CRediT authorship contribution statement:-

FUGA: Conceptualization, Methodology, Validation, Visualization, Writing – original draft, Writing – reviewing & editing;**RBT**: conceptualization, methodology, investigation, formal analysis, Writing – reviewing & editing;**IBC**: conceptualization, methodology, Writing – reviewing & editing;**JMK**: conceptualization, methodology, Writing – reviewing & editing;**CNAS:**conceptualization,methodology,Writingreviewing&editing;**FH:**Supervision,Conceptualization, Methodology, Writing – reviewing & editing;**APPK:** conceptualization, methodology, Writing – reviewing & editing.

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Ethical statement:-
This study involved interviewing participants in Banikoara.

Declaration of competing interest:-
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability:-
Data will be available on request.

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