Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Machine learning based Prediction of Severe Child Food Poverty and Associated Factors among Children Aged 6–23 Months in Ethiopia

Selamawite Fekadie Tewoligne

selamewitefekadie@gmail.com

Debre Tabour University

Dejen Kahsay Asgedom

Samara University

Degsew Ewunetie Anteneh

Woldia University

Mulualem Endeshaw Zeleke

University of Gondar

Alemken Eyayu Abuhay

University of Gondar Comprehensive Specialized Referral Hospital

Berihun Agegn Mengistie

University of Gondar

Haymanot Nega Alemu

University of Gondar

Kindu Yinges Wondie

University of Gondar

Tazeb Alemu Anteneh

University of Gondar

Amare Belete Getahun

University of Gondar

Jenberu Mekurianew Kelkay

Debark University

Halima Ayalew Kebede

Woldia University

Abraham Keffale Mengistu

Debre Markos University

Andualem Enyew Gedefaw

University of Gondar

Tadele Chekol Maru

University of Gondar

Fentahun Bikale Kebede

Federal Ministry of Health

Makda Fekadie Tewelgne

University of Gondar

Research Article

Keywords:

Posted Date: November 16th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11348716/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Machine learning based Prediction of Severe Child Food Poverty and Associated Factors among Children Aged 6–23 Months in Ethiopia

Selamawite Fekadie Tewoligne[1*],Dejen Kahsay Asgedom[2], Degsew Ewunetie Anteneh[3],Mulualem Endeshaw Zeleke[4],Alemken Eyayu Abuhay[5],Berihun Agegn Mengistie[6],Haymanot Nega Alemu[7], Kindu Yinges Wondie[7], Tazeb Alemu Anteneh[7], Amare Belete Getahun[8],Jenberu Mekurianew Kelkay[9],Halima Ayalew Kebede[10], Abraham Keffale Mengistu [11], Andualem Enyew Gedefaw[12], Tadele Chekol Maru[12], Fentahun Bikale Kebede[13] Makda Fekadie Tewelgne[12]

[1]Department of Neonatal, College of Medicine and Health Sciences, Debre Tabour University, Debre Tabour, Ethiopia

[2]Department of Public Health, College of Medicine and Health Science, Samara University, Samara, Ethiopia

[3]Department of Clinical Midwifery, School of Midwifery, College of Medicine and Health Science, Woldia University, Woldia, Ethiopia

[4]Department of Anesthesia, College of Medicine and Health Sciences, University of Gondar, Gondar, Ethiopia

[5]Department of Clinical Midwifery, College of Medicine and Health Sciences, University of Gondar Comprehensive Specialized Referral Hospital, Gondar, Ethiopia

[6]Department of General Midwifery, School of Midwifery, College of Medicine and Health Sciences, University of Gondar, Gondar, Ethiopia

[7]Department of Clinical Midwifery, School of Midwifery, College of Medicine and Health Sciences, University of Gondar, Gondar, Ethiopia

[8]Department of Anesthesia, School of Medicine, College of Medicine and Health sciences, University of Gondar, Gondar, Ethiopia

[9]Department of Public Health, College of Health Sciences, Debark University, Debark, Ethiopia

[10]Department of Public Health, College of Health Sciences, Woldia University, Woldia, Ethiopia.

[11]Department of Health Informatics, College of Medicine and Health Sciences, Debre Markos University, Debre Markos, Ethiopia

[12]Department Health informatics, Institute of Public Health, College of Medicine and Health Sciences, University of Gondar, Gondar, Ethiopia

[13] Strategic Affairs Executive Office, Federal Ministry of Health, Addis Ababa, Ethiopia

*Corresponding author

Selamawite Fekadie Tewoligne

Email: selamewitefekadie@gmail.com

Email-
selamewitefekadie@gmail.com,dejenk2@gmail.com,degsewewunetie@gmail.com,muleaman45@gmail.com,alexeyayu6@gmail.com,berihunagegn21@gmail.com,haymnigat@gmail.com,kinduyinges2010@gmail.com,tazebalemu05@gmail.com,amarebelete2218@gmail.com,jenberu.uog11@gmail.com,halimaayalew0977@gmail.com,keffaleabrahame2@gmail.com,andualemenyew

@gmail.com,tadelle2007@gmail.com,fentahunbikale09@gmail.com,makdafekadeal@gmail.com

Abstract

Background: Severe child food poverty is a significant nutritional concern, particularly during the complementary feeding period of 6–23 months, when inadequate dietary diversity can adversely affect child growth and development. Identifying children at greater risk may support timely and targeted nutrition interventions. This study aimed to predict severe child food poverty using machine learning models and identify its associated factors among children aged 6–23 months in Ethiopia.

Methods: A nationally representative sample of 3,792 children aged 6–23 months from the 2024-25 Ethiopia Demographic and Health Survey was analyzed. Severe child food poverty was defined as consumption of foods from 0–2 of eight recommended food groups during the preceding 24 hours. Descriptive and inferential analyses were conducted to identify associated factors. Seven machine learning algorithms—Random Forest, XGBoost, Decision Tree, Artificial Neural Network, LightGBM, K-Nearest Neighbors, and Logistic Regression—were developed and evaluated. The training data were balanced using SMOTE, while tenfold cross-validation and RandomizedSearchCV were used for model tuning. Model performance was assessed using accuracy, precision, recall, F1-score, ROC-AUC, and PR-AUC.

Results: Among the 3,792 children aged 6–23 months, 1,780 (46.94%) experienced severe child food poverty. Child age, mass-media exposure, maternal education, wealth index, maternal age household size, and antenatal care attendance were significantly associated with severe child food poverty. Children aged 6–11 months, those from poorer households and larger households,

and those born to younger or less-educated mothers had higher likelihood of severe food poverty. In contrast, greater maternal mass-media exposure and adequate ANC attendance were associated with lower likelihood of severe food poverty. Among the evaluated machine learning models, Random Forest showed the best predictive performance, achieving 93.54% accuracy, 93.61% precision, 93.49% recall, and 93.53% F1-score, followed by XGBoost and Decision Tree.

Conclusion: Severe child food poverty affected nearly half of children aged 6–23 months in Ethiopia. The strong performance of Random Forest demonstrates the potential of machine learning to identify children at high risk of severe food poverty and to capture complex relationships among maternal, household, and child-related factors. Integrating predictive approaches with targeted nutrition interventions may help improve dietary adequacy during the critical complementary feeding period.

Introduction

Child food poverty has emerged as an important global nutrition concern, with the United Nations Children's Fund (UNICEF) highlighting the widespread deprivation of diverse, nutritious, and age-appropriate foods among young children (1, 2). It refers to inadequate access to and consumption of diverse and nutritious foods among children aged 6–23 months, assessed using the UNICEF–WHO framework across eight food groups, where consumption of at least five groups meets minimum dietary diversity, three to four groups indicates child food poverty, and zero to two groups indicates severe child food poverty (1, 3).

Child food poverty has emerged as a major global public health concern, affecting an estimated 440 million children under five in 2024, including approximately 181 million experiencing

severe child food poverty—nearly one in four children worldwide (4). The burden is disproportionately concentrated in South Asia and sub-Saharan Africa, which together account for a large proportion of children experiencing severe child food poverty (1, 4). In East Africa, child food poverty remains a substantial public health challenge, with Ethiopia reporting that approximately 46% of children under five years' experience severe child food poverty and 92% experience either moderate or severe child food poverty (1, 5). However, substantial regional variation exists within Ethiopia, with severe child food poverty reported at particularly high levels in Somali (75%), Tigray (62%), Afar (50%), Amhara (50%), and Sidama (48%), while lower levels have been reported in Addis Ababa, highlighting important geographic inequalities in children's access to diverse and nutritious diet (5-8).

For children aged 6–23 months, adequate dietary diversity is particularly important because this period represents a critical stage of complementary feeding, with essential implications for physical growth, brain development, immune function, and long-term health (9, 10). "Children experiencing severe food poverty may have limited access to nutrient-dense foods such as eggs, dairy products, meat, fish, fruits, vegetables, legumes, nuts, and seeds, increasing their risk of micronutrient deficiencies, impaired growth, weakened immunity, and poor developmental outcomes (9, 11-16). According to UNICEF, these children are up to 50% more likely to suffer from wasting, a life-threatening form of acute malnutrition (1). The consequences of inadequate nutrition during early childhood may extend into later life, affecting educational attainment, productivity, health, and human capital development (1, 7, 17, 18).

Although household economic conditions are important, child food poverty is not determined by wealth alone. UNICEF estimates that a substantial proportion of children experiencing severe child food poverty live in households outside the poorest wealth group, indicating that maternal,

child, household, and contextual characteristics also contribute to dietary deprivation (1, 19, 20). Previous studies have identified factors such as maternal education, maternal age, antenatal care utilization, household wealth, household size, child age, media exposure, maternal nutrition knowledge, place of residence, and access to health and nutrition services as important factors related to child dietary diversity and feeding practices (1, 5-7, 18, 21). In addition, environmental and climatic conditions may influence food availability and household access to diverse foods, particularly in vulnerable communities (22-24).

Despite the considerable burden of severe child food poverty in Ethiopia, evidence based on recent nationally representative data remains limited, and most previous studies have relied on conventional statistical methods to examine individual associations. Such approaches may be less effective in capturing complex, nonlinear, and interactive relationships among multiple child, maternal, household, and socioeconomic characteristics. Machine learning offers an alternative approach that can identify complex predictive patterns across multiple variables and may improve the identification of children at higher risk of severe food poverty. However, the application of machine learning to predict severe child food poverty among Ethiopian children aged 6–23 months remains limited, particularly using the recent 2024–25 EDHS data. Therefore, this study aimed to develop and compare machine learning models for predicting severe child food poverty and to identify the most important predictive factors among children aged 6–23 months in Ethiopia using the 2024–25 EDHS. Furthermore, explainable machine learning techniques were used to improve the interpretation of model predictions and provide insight into the contribution of individual predictors.

Methods

Study Design and Setting

A secondary cross-sectional study was conducted in Ethiopia using nationally representative survey data. Ethiopia is located in the Horn of Africa in East Africa and is bordered by Eritrea to the north, Djibouti and Somalia to the east, Kenya to the south, South Sudan to the west, and Sudan to the northwest. The country is characterized by substantial geographic, socioeconomic, and cultural diversity, with differences in living conditions and access to food and essential services across regions and between urban and rural areas.

The target population for this study was children aged 6–23 months in Ethiopia. This age group was selected because it represents the complementary-feeding period, during which adequate food intake and dietary diversity are particularly important for child growth, development, and health.

Study Population and Data Sources

Data for this study were obtained from the 2024–25 Ethiopia Demographic and Health Survey (EDHS) Kids Recode (KR) dataset. The KR dataset contains child-level information collected through standardized DHS questionnaires, including dietary consumption, child characteristics, maternal characteristics, household socioeconomic conditions, and other relevant factors.

The 2024–25 EDHS employed a stratified two-stage cluster sampling design to obtain nationally representative data. In the first stage, enumeration areas were selected from the sampling frame, while households were systematically selected from the sampled enumeration areas in the second

stage (48). Information on eligible children and their mothers was collected using standardized survey procedures.

For descriptive and prevalence analyses, DHS sampling weights (v005), stratification, and clustering variables were applied in accordance with DHS analytical guidelines to account for the complex survey design and obtain nationally representative estimates. Sampling weights were normalized by dividing by 1,000,000 as recommended for DHS analyses.

For machine learning analyses, sampling weights were not incorporated during model training because the primary objective was individual-level prediction rather than population-level inference. Therefore, each eligible child was treated as an individual observation during model development.

After applying the predefined eligibility criteria and data preprocessing procedures, including data cleaning and handling of missing information, the final analytic sample comprised 3,792 children aged 6–23 months.

Inclusion and Exclusion Criteria

Children aged 6–23 months who were included in the 2024–25 Ethiopia Demographic and Health Survey (EDHS) Kids Recode (KR) dataset were eligible for inclusion. Children were included if sufficient information was available to determine their severe child food poverty status and relevant predictor variables.

Children younger than 6 months or older than 23 months were excluded from the analysis. Children with missing or invalid information required to determine the severe child food poverty outcome were also excluded. Missing values in predictor variables were addressed during the

data preprocessing stage using appropriate imputation techniques rather than excluding children solely because of missing predictor information.

After applying the eligibility and exclusion criteria, the final analytic sample consisted of 3,792 children aged 6–23 months.

Study Variables

Severe child food poverty was the primary outcome variable. Severe child food poverty was defined as consumption of foods and beverages from zero, one, or two of the eight UNICEF/WHO-defined food groups during the previous 24 hours (25, 26). The eight food groups were: (1) breast milk; (2) grains, roots, tubers, and plantains; (3) pulses, nuts, and seeds; (4) dairy products; (5) flesh foods, including meat, poultry, and fish; (6) eggs; (7) vitamin A-rich fruits and vegetables; and (8) other fruits and vegetables. Children who consumed foods or beverages from 0–2 food groups were classified as experiencing severe child food poverty (coded 1), while those who consumed foods or beverages from three or more food groups were classified as not experiencing severe child food poverty (coded 0).

The Independent variables were grouped into child-level, maternal-level, and household-level characteristics. Child-level variables included child sex, age, birth order, birth interval, birth weight, breastfeeding status, and number of children under five years. Maternal-level variables included maternal age, education, employment status, antenatal care visits, place of delivery, skilled birth attendance, postnatal care, maternal anemia, and household decision-making. Household-level variables included wealth index, household size, place of residence, religion, and region. All variables were defined and coded according to standard DHS definitions and recode manuals to ensure clarity, consistency, and reproducibility (27).

Operational Definition

Severe child food poverty: Children who consumed foods and/or beverages from 0–2 of the eight food groups during the previous 24 hours were classified as experiencing severe child food poverty, while those who consumed foods from three or more food groups were classified as not experiencing severe child food poverty.

Food groups: The eight food groups were grains, roots and tubers; pulses, nuts and seeds; dairy products; flesh foods; eggs; vitamin A-rich fruits and vegetables; other fruits and vegetables; and breast milk.

Child age: Age of the child in completed months, restricted to children aged 6–23 months.

Minimum dietary diversity: A child was considered to have achieved minimum dietary diversity if foods from at least five of the eight food groups were consumed during the previous 24 hours.

Ethical Considerations and Data Access

Permission to access the 2024–25 Ethiopia Demographic and Health Survey (EDHS) dataset was obtained through the DHS Program after submission of a formal data access request and study description. The dataset used for this study was de-identified, and no personally identifiable information was accessed or reported.

The original EDHS survey was conducted in accordance with established ethical standards, including informed consent, confidentiality, and protection of participants' privacy. As this study involved secondary analysis of de-identified survey data, no direct contact with participants was undertaken. All analyses were conducted in accordance with the DHS data-use requirements and

policies, and the findings are reported only in aggregate form to protect participant confidentiality.

Data Pre-Processing

Data Splitting

Before machine learning model development, the final analytical dataset was divided into training and testing sets using an 80:20 ratio. The training set comprised approximately 80% of the observations (n = 3,033), while the remaining 20% (n = 759) were reserved as an independent testing set. The training set was used for model development, feature selection, hyperparameter tuning, and cross-validation, while the independent testing set was reserved exclusively for evaluating the final model performance on unseen data. Stratified sampling was used to maintain a similar distribution of severe child food poverty cases and non-cases in both datasets. The data splitting was performed before applying class-imbalance correction techniques to prevent information leakage between the training and testing datasets. A fixed random state was used to ensure reproducibility of the results.

Data Cleaning

Data cleaning was performed to identify duplicate records, inconsistent responses, coding errors, and implausible values using the DHS coding and recode specifications (28).

Missing values in predictor variables were handled using median imputation for continuous variables and mode imputation for categorical variables. Imputation was performed using the training data only and subsequently applied to the test data to prevent data leakage. The cleaned dataset was then used for subsequent data transformation and machine learning analysis.

Data Transformation

Categorical predictor variables were converted into numerical representations using one-hot encoding, while continuous variables were standardized using z-score normalization where required. All transformations were fitted using the training data and subsequently applied to the testing data to prevent data leakage.

Data Discretization

Data discretization was selectively applied to convert continuous variables into meaningful categories, improve interpretability, and facilitate subsequent analysis (29). Continuous variables were discretized into meaningful categories based on established DHS classifications, statistical considerations, and relevant public health thresholds (27). For example, child age was categorized as 6–11, 12–17, and 18–23 months, while maternal age was grouped as 15–19, 20–24, 25–34, and 35–49 years (27). This approach improved the interpretability of the categorized variables and facilitated subsequent statistical and machine-learning analyses.

Feature Selection

Feature selection was performed to identify the most relevant predictors while reducing dimensionality, minimizing redundancy, and improving model efficiency (30).

Recursive Feature Elimination (RFE) was used to iteratively remove the least important features based on model performance and retain the optimal subset of predictors(31). A 10-fold cross-validation approach was applied to determine the optimal number of features for subsequent machine-learning analyses.

Data Analysis Procedure

Data analysis was conducted using Stata 17 and Python 3.12.13. Python libraries, including scikit-learn, pandas, NumPy, XGBoost, LightGBM, imbalanced-learn, SHAP, and Matplotlib, were used for data preprocessing, model development, evaluation, and visualization. Seven supervised machine-learning algorithms—Random Forest (RF), Logistic Regression (LR), Decision Tree (DT), K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), Light Gradient Boosting Machine (LightGBM), and Extreme Gradient Boosting (XGBoost)—were developed to predict preterm birth. SMOTE was applied only to the training data to address class imbalance, while Recursive Feature Elimination (RFE) with 10-fold cross-validation was used for feature selection. Model performance was evaluated using accuracy, precision, recall, F1-score, and ROC-AUC. SHAP was applied after model training to explain feature contributions and enhance model interpretability. Random seeds were fixed at 42 to ensure reproducibility, and preprocessing and resampling were restricted to the training data to prevent data leakage. The overall analytical workflow, including data preprocessing, feature selection, class imbalance handling, model development, evaluation, calibration, and SHAP-based interpretation, is presented in Figure 1.

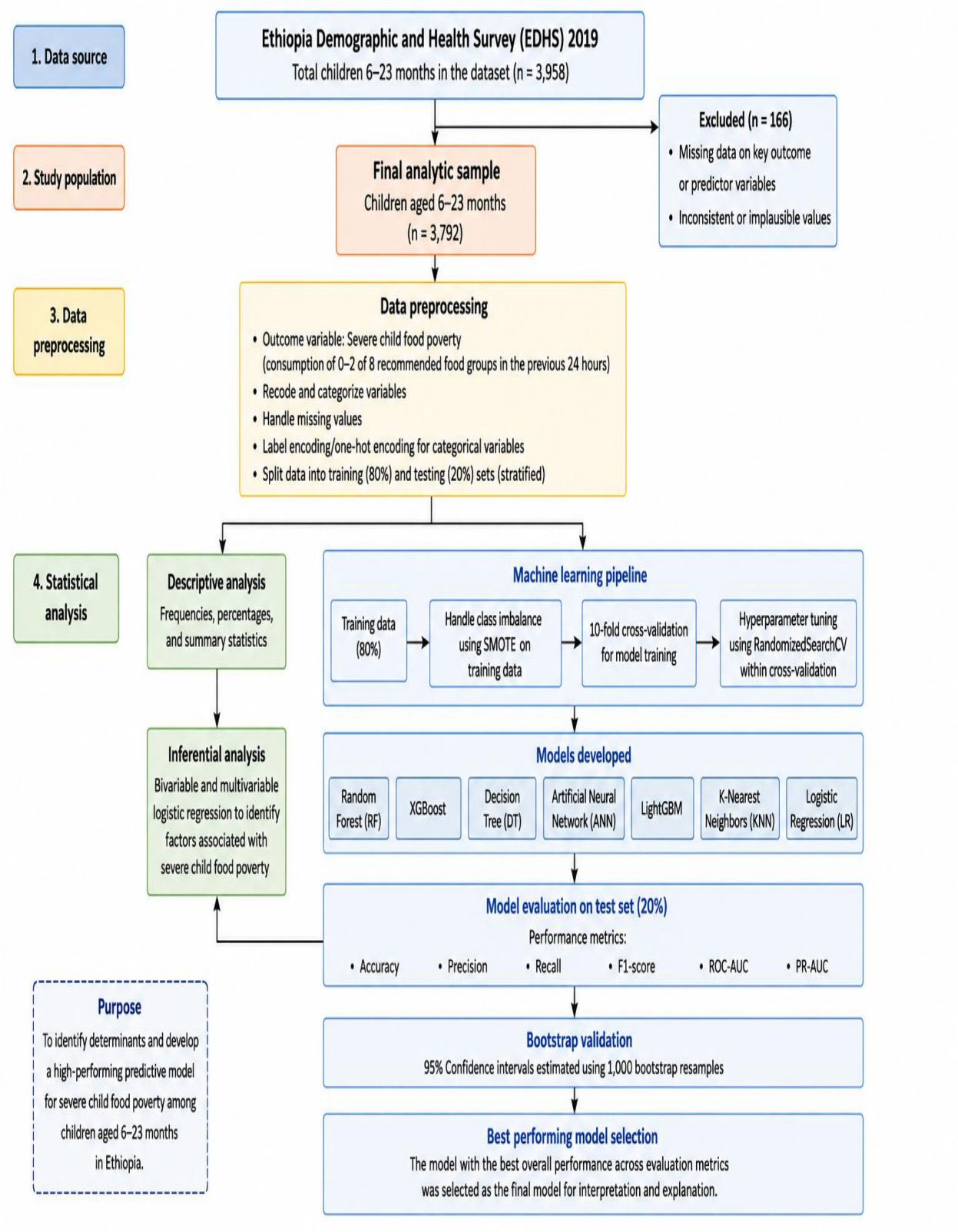


Figure 1 Study Workflow Diagram

Class Balancing

Class balancing was performed to reduce potential bias toward the majority class in predicting severe child food poverty. The Synthetic Minority Over-sampling Technique (SMOTE) was applied exclusively to the training data. SMOTE generates synthetic minority-class observations by interpolating between existing minority samples and their nearest neighbors. In this study, k = 5 nearest neighbors and Euclidean distance were used for synthetic sample generation (32). This approach improved minority-class representation without simply duplicating existing observations.

Model Selection and Development

To predict severe child food poverty and identify influential predictors, seven machine-learning algorithms were implemented in Python (v3.12.13) using the Scikit-learn framework. The selected models were Random Forest (RF), Logistic Regression (LR), Decision Tree (DT), K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), LightGBM, and XGBoost. These algorithms were selected for their ability to capture different patterns and relationships within the data. All models used the same preprocessing procedures and train–test split, with SMOTE applied only to the training data. Model performance was evaluated on the independent test set using consistent performance metrics, enabling a fair comparison of the algorithms and selection of the best-performing model.

Model Training

After data cleaning and preprocessing, 3,792 children aged 6–23 months were included in the analysis. The data were stratified into training (80%; n = 3,034) and testing (20%; n = 758) sets.

Ten-fold cross-validation was performed on the training set, with nine folds used for model training and one fold for validation in each iteration. Performance across the folds was averaged to obtain robust estimates of model performance. The final models were evaluated on the independent test set to provide an unbiased assessment of predictive performance.

Model Evaluation

Model performance was evaluated using an independent hold-out test set to assess prediction on unseen data. Accuracy, precision, recall, F1-score, ROC-AUC, and PR-AUC were used to evaluate predictive performance. Accuracy measured the proportion of correctly classified observations, while precision, recall, and F1-score assessed classification performance for the severe child food poverty outcome. ROC-AUC evaluated overall discrimination across classification thresholds, while PR-AUC provided additional assessment of performance under class imbalance. All models were evaluated using the same test dataset and metrics to ensure a fair comparison of predictive performance.

Hyper Parameter Tuning

Hyperparameter tuning was performed to optimize the predictive performance of the machine-learning models. RandomizedSearchCV with 10-fold cross-validation was applied exclusively to the training dataset, using ROC-AUC as the optimization metric. The search included model-specific parameters for Random Forest, Logistic Regression, Decision Tree, K-Nearest Neighbors, Artificial Neural Network, LightGBM, and XGBoost. The optimal hyperparameters were selected based on the highest cross-validated ROC-AUC score for each model. The independent test set was kept completely separate from the tuning process and was used only for final model evaluation.

Results

This section presents the socio-demographic and household characteristics of the study participants. The distribution of maternal, household, and child-related characteristics provides an overview of the study population and describes the main characteristics considered in the analysis of severe child food poverty

Child-Level Characteristics

The study included 3,792 children aged 6–23 months. Regarding child characteristics, males accounted for 51.58% (n=1,956) of the study population, while females accounted for 48.42% (n=1,836). Children aged 12–17 months constituted the largest age group (36.05%, n=1,367), followed by those aged 6–11 months (34.78%, n=1,319) and 18–23 months (29.17%, n=1,106). Regarding birth order, 42.62% (n=1,616) were fourth-born or later, 35.57% (n=1,349) were second- or third-born, and 21.81% (n=827) were first-born. More than one-third of children (38.92%, n=1,476) had a birth interval of 24–47 months, while 36.18% (n=1,372) had an interval of less than 24 months and 24.89% (n=944) had an interval of at least 48 months. Most children were reported to have a birth weight below 2,500 g (95.70%, n=3,629), and 19.96% (n=757) were currently breastfeeding. In addition, 57.59% (n=2,184) of children lived in households with two or more children under five years of age (table 1).

Table 1 Distribution of child-level independent variables among children aged 6–23 months (N = 3,792)

Child-level independent variable	Classification	Frequency	Percentage
Child sex	Male	1,956	51.58
	Female	1,836	48.42
Child age	6-11	1,319	34.78
	12-17	1,367	36.05
	18-23	1,106	29.17
Birth order	1st	827	21.81
	2nd–3rd	1,349	35.57
	≥4th	1,616	42.62
Birth interval	<24 months	1,372	36.18
	24–47 months	1,476	38.92
	≥48 months	944	24.89
Birth weight	<2,500 g	3,629	95.70
	≥2,500 g	163	4.30
Breastfeeding status	Currently breastfeeding	757	19.96
	Not currently breastfeeding	3,035	80.04
Number of children under 5 years	0–1 child	1,608	42.41
	≥2 children	2,184	57.59

Maternal characteristics

Maternal characteristics showed that more than half of the mothers were aged 25–34 years (53.09%, n=2,013), followed by those aged 20–24 years (21.10%, n=800), 35–49 years (20.75%, n=787), and 15–19 years (5.06%, n=192). In terms of education, 40.64% (n=1,541) of mothers had no formal education, 35.63% (n=1,351) had primary education, 14.16% (n=537) had secondary education, and 9.57% (n=363) had higher education. Most mothers were not working (72.13%, n=2,735), while 27.87% (n=1,057) were employed. Regarding maternal BMI, 63.48%

(n=2,407) were underweight, 31.41% (n=1,191) had normal BMI, and 5.12% (n=194) were overweight or obese. ANC utilization varied across mothers: 25.34% (n=961) had no ANC visits, 24.68% (n=936) had 1–3 visits, 28.72% (n=1,089) had 4–7 visits, and 21.26% (n=806) had eight or more visits. More than half of deliveries occurred in health facilities (56.22%, n=2,132), and 56.9% (n=2,161) of births were attended by a skilled birth attendant. However, child postnatal care/check was low, with only 10.39% (n=394) receiving a postnatal check. About one-third of mothers (34.92%, n=1,324) had media exposure, while 65.08% (n=2,468) had no reported media exposure. The majority of mothers were married or in union (94.65%, n=3,589), while 5.35% (n=203) were not married or in union **(table 2).**

Table 2 Distribution of Maternal Characteristics Among Children Aged 6–23 Months in Ethiopia (N = 3,792)

Maternal factor	Classification	Frequency	Percentage
Maternal age	15–19 years	192	5.06
	20–24 years	800	21.10
	25–34 years	2,013	53.09
	35–49 years	787	20.75
Maternal education	No education	1,541	40.64
	Primary	1,351	35.63
	Secondary	537	14.16
	Higher	363	9.57
Maternal _employment	Not working	2,735	72.13
	Working	1,057	27.87
Maternal BMI	Underweight (<18.5)	2,407	63.48
	Normal (18.5–24.9)	1,191	31.41
	Overweight/Obese	194	5.12
ANC utilization	No ANC	961	25.34
	1–3 visits	936	24.68
	4–7 visits	1,089	28.72

Maternal factor	Classification	Frequency	Percentage
	≥8 visits	806	21.26
Place of delivery	Home	1,660	43.78
	Health facility	2,132	56.22
Skilled birth attendance	No skilled birth attendance	1,631	43.0
	Skilled birth attendance	2,161	56.9
Child postnatal care/check	No child PNC check	3,398	89.61
	Child PNC check	394	10.39
Media exposure	No	2,468	65.08
	Yes	1,324	34.92
marital status	Not married/in union	203	5.35
	Married/in union	3,589	94.65
Religion	Orthodox	1,059	27.93
	catholic	26	0.69
	protestant	1,017	26.82
	Muslim	1,599	42.17
	traditional	25	0.66
	other	66	1.74

Household characteristics

Household characteristics indicated that more than half of the children (53.16%, n=2,016) lived in households in the poorest wealth category, while 33.12% (n=1,256) were in the rich category and 13.71% (n=520) were in the middle category. Most children lived in rural households (70.60%, n=2,677), whereas 29.40% (n=1,115) lived in urban households. Regarding household size, 46.78% (n=1,774) were from medium-sized households, 32.59% (n=1,236) from small households, and 20.62% (n=782) from large households. Most households were headed by males (78.56%, n=2,979), while 21.44% (n=813) were headed by females. Regarding paternal education, 36.50% (n=1,384) had no education, 31.36% (n=1,189) had primary education,

18.51% (n=702) had secondary education, and 13.63% (n=517) had higher education. Most husbands/partners were working (77.37%, n=2,934), while 22.63% (n=858) were not working.

With respect to household living conditions, 58.91% (n=2,234) of households had access to an improved water source, while 41.09% (n=1,558) used unimproved water sources. Similarly, 78.06% (n=2,960) had improved sanitation facilities and 21.94% (n=832) had unimproved facilities. Electricity was available in 55.72% (n=2,113) of households, whereas 44.28% (n=1,679) had no electricity access. Overall, the descriptive findings indicate substantial variation in maternal healthcare utilization, socioeconomic status, household living conditions, and child-related characteristics, providing an important basis for predicting severe child food poverty among children aged 6–23 months (Table 3).

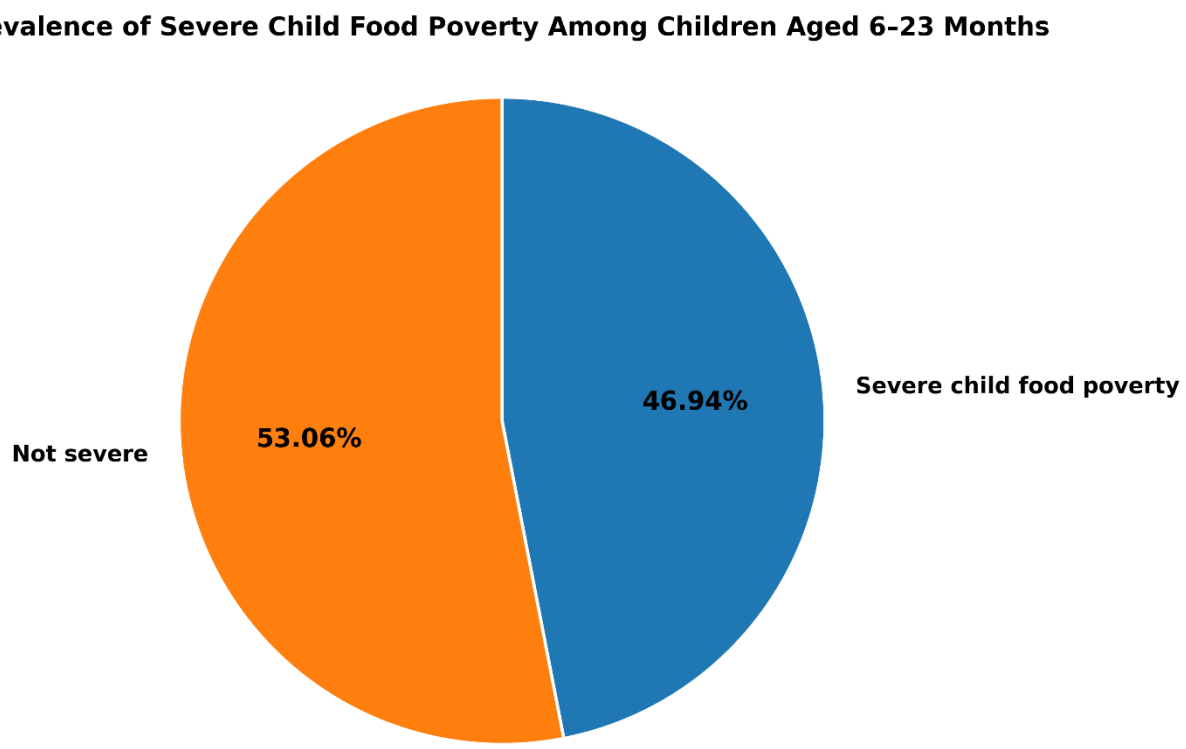
Table 3 Distribution of Household and Environmental Characteristics among Children Aged 6–23 Months in Ethiopia (N = 3,792)

Household factor	Classification	Frequency	Percentage
Household wealth	Poorest	2,016	53.16
	Middle	520	13.71
	Rich	1,256	33.12
Place of residence	Rural	2,677	70.60
	Urban	1,115	29.40
Household size	Small	1,236	32.59
	Medium	1,774	46.78
	Large	782	20.62
Sex of household head	Male	2,979	78.56
	Female	813	21.44
Father Education	No education	1,384	36.50
	Primary	1,189	31.36
	Secondary	702	18.51
	Higher	517	13.63

husband occupation	Not working	858	22.63
	Working	2,934	77.37
Water source	Unimproved	1,558	41.09
	Improved	2,234	58.91
Sanitation facility	Unimproved	832	21.94
	Improved	2,960	78.06
Electricity access	No	1,679	44.28
	Yes	2,113	55.72
Toilet	Unimproved	2,167	57.15
	Improved	1,625	42.85
Region	Tigray	337	8.89
	Afar	380	10.02
	Amhara	279	7.36
	Oromia	392	10.34
	Somali	393	10.36
	Benishangul-gumuz	248	6.54
	Central Ethiopia	278	7.33
	Sidama	243	6.41
	South West Ethiopia	236	6.22
	South Ethiopia	288	7.59
	Gambella	215	5.67
	Harari	156	4.11
	Addis Ababa	180	4.75
	Dire Dawa	167	4.40

Class Balancing

Among the 3,792 children aged 6–23 months, 1,780 (46.94%) were classified as experiencing severe child food poverty, while 2,012 (53.06%) were not (Figure 2). The relatively balanced distribution between the two outcome classes indicates that class imbalance was limited in the study dataset. Nevertheless, SMOTE was applied exclusively to the training data to improve the representation of the minority class during model development. Using k = 5 nearest neighbors, SMOTE generated synthetic observations by interpolating between existing minority-class samples rather than duplicating observations. This approach supported balanced model learning while ensuring that the independent test dataset remained unchanged for unbiased evaluation.



400

401 **Figure 2 Prevalence of severe child food poverty among children aged 6–23 months in**
402 **Ethiopia (N = 3,792).**

403 **Feature Importance and Selection**

404 Feature selection was performed using Recursive Feature Elimination (RFE) with 10-fold cross-
405 validation to identify the most informative predictors for severe child food poverty. Random
406 Forest feature importance was subsequently used to assess the relative contribution of the
407 predictors to model performance. As shown in Figure 3, ANC visits had the highest feature
408 importance (0.071), followed by child age (0.067), father's education (0.066), maternal age
409 (0.062), and breastfeeding status (0.060). Other relatively important predictors included maternal
410 education (0.054), household size (0.052), birth interval (0.051), maternal BMI (0.049), and birth
411 order (0.045). Wealth status (0.037), maternal employment (0.034), water source (0.033), and

number of children (0.033) also contributed to model predictions. Variables such as marital status (0.008), birth weight (0.010), place of delivery (0.018), and skilled birth attendance (0.020) showed comparatively lower importance. These importance scores represent model-based predictive contributions and should not be interpreted as causal effects.

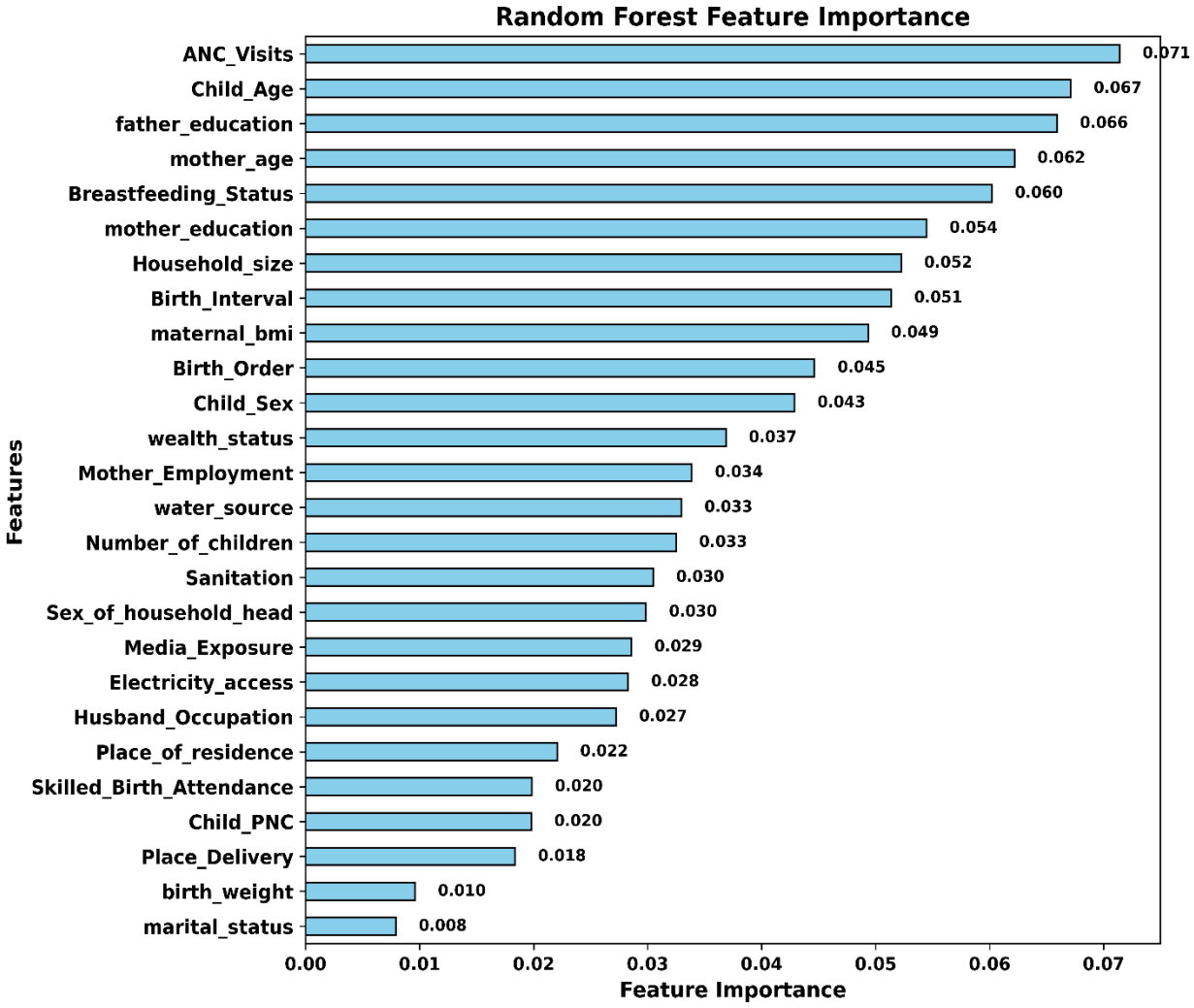


Figure 3 Random Forest feature importance ranking for predicting severe child food poverty among children aged 6–23 months.

Development and performance comparison of machine learning models

Multiple supervised machine learning algorithms were systematically evaluated to predict severe child food poverty. To improve model generalizability and optimize predictive performance, tenfold cross-validation was combined with RandomizedSearchCV for hyperparameter tuning. The evaluated models included Random Forest (RF), XGBoost, Decision Tree (DT), Artificial Neural Network (ANN), LightGBM, K-Nearest Neighbors (KNN), and Logistic Regression (LR). The models were trained using the SMOTE-balanced training dataset and evaluated on the original test dataset. Model performance was assessed using accuracy, precision, recall (sensitivity), and F1-score. Ninety-five percent confidence intervals (CIs) were estimated using 1,000 bootstrap iterations for each performance metric to quantify statistical uncertainty.

As presented in Table 4, Random Forest demonstrated the highest predictive performance, with an accuracy of 93.54% (95% CI: [accuracy CI]), precision of 93.61% (95% CI: [precision CI]), recall of 93.49% (95% CI: [recall CI]), and F1-score of 93.53% (95% CI: [F1 CI]). XGBoost demonstrated the second-highest performance, with an accuracy of 92.62% (95% CI: [accuracy CI]), precision of 92.64% (95% CI: [precision CI]), recall of 92.59% (95% CI: [recall CI]), and F1-score of 92.62% (95% CI: [F1 CI]). Decision Tree achieved an accuracy of 91.96% (95% CI: [accuracy CI]), precision of 91.95% (95% CI: [precision CI]), recall of 91.96% (95% CI: [recall CI]), and F1-score of 91.96% (95% CI: [F1 CI]).

ANN achieved an accuracy of 88.41% (95% CI: [accuracy CI]), precision of 88.39% (95% CI: [precision CI]), recall of 88.42% (95% CI: [recall CI]), and F1-score of 88.40% (95% CI: [F1 CI]). LightGBM achieved an accuracy of 83.66% (95% CI: [accuracy CI]), precision of 83.69% (95% CI: [precision CI]), recall of 83.61% (95% CI: [recall CI]), and F1-score of 83.63% (95%

CI: [F1 CI]). KNN achieved an accuracy of 78.22% (95% CI: [accuracy CI]), precision of 75.52% (95% CI: [precision CI]), recall of 74.00% (95% CI: [recall CI]), and F1-score of 72.95% (95% CI: [F1 CI]). Logistic Regression showed the lowest performance, with an accuracy of 73.37% (95% CI: [accuracy CI]), precision of 72.45% (95% CI: [precision CI]), recall of 73.16% (95% CI: [recall CI]), and F1-score of 70.07% (95% CI: [F1 CI]).

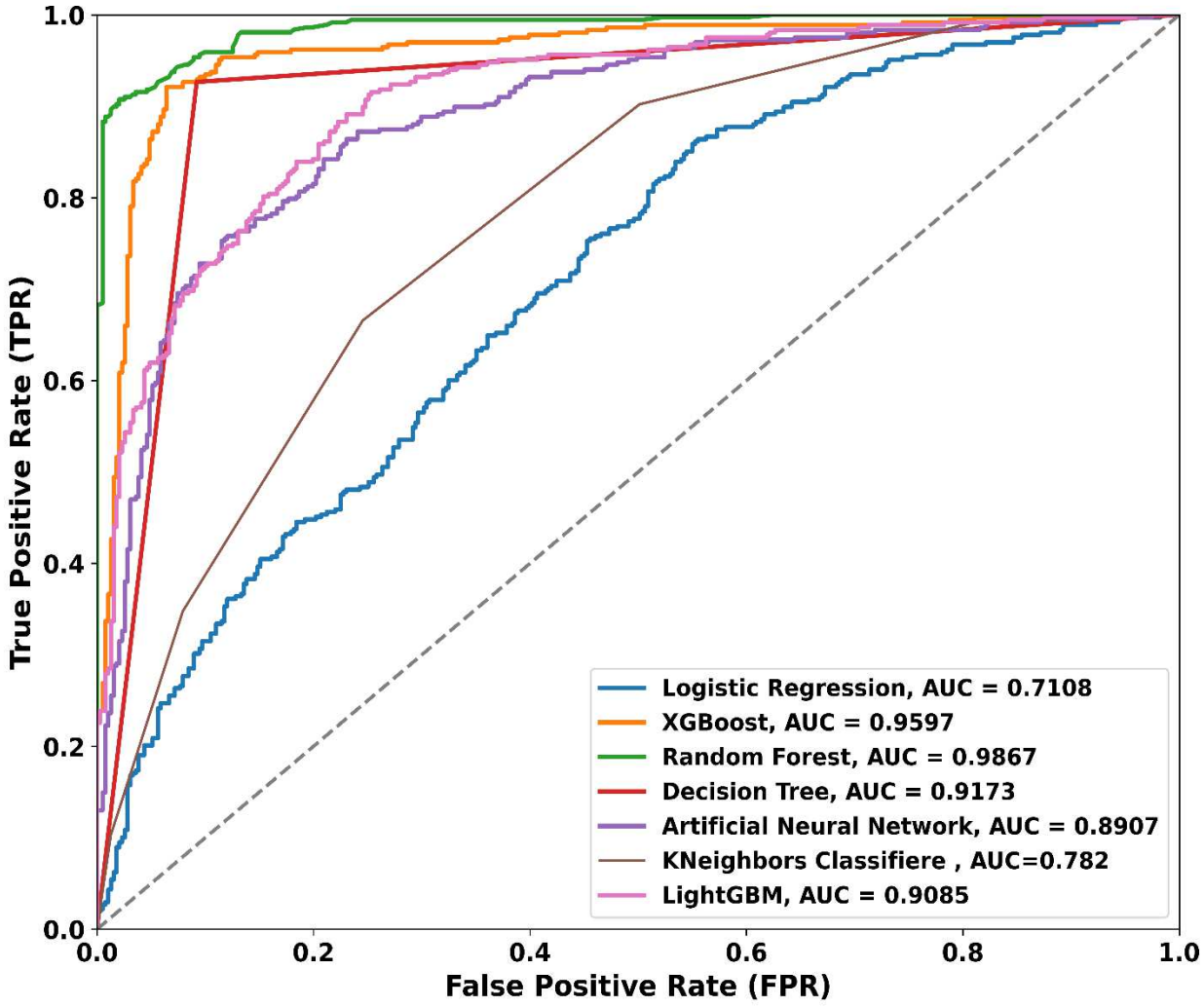
Overall, Random Forest demonstrated the strongest predictive performance across all evaluation metrics, followed by XGBoost and Decision Tree. ANN and LightGBM showed moderate predictive performance, whereas KNN and Logistic Regression demonstrated comparatively lower performance. The confidence intervals provide information on the statistical uncertainty of each model's performance estimates and support a more robust comparison across algorithms. The superior performance of Random Forest may be attributed to its ensemble architecture, which combines multiple decision trees and captures nonlinear relationships and interactions among predictors while reducing variance. Based on its consistently superior performance, Random Forest was selected as the final model for subsequent interpretation and explanation. The comparative performance of all models is presented in Table 4, while the corresponding ROC and precision–recall curves are presented in Figures 4 and 5, respectively

Table 4 Final model performance comparison of machine learning models for predicting severe child food poverty.

Model	Accuracy	Precision	Recall	F1-score
Random Forest (RF)	**93.54%**	**93.61%**	**93.49%**	**93.53%**
XGBoost	92.62%	92.64%	92.59%	92.62%
Decision Tree (DT)	91.96%	91.95%	91.96%	91.96%

Model	Accuracy	Precision	Recall	F1-score
ANN	88.41%	88.39%	88.42%	88.40%
LightGBM	83.66%	83.69%	83.61%	83.63%
KNN	78.22%	75.52%	74.00%	72.95%
Logistic Regression (LR)	73.37%	72.45%	73.16%	70.07%

460



461

462 **Figure 4 ROC-AUC curve score of machine learning model**

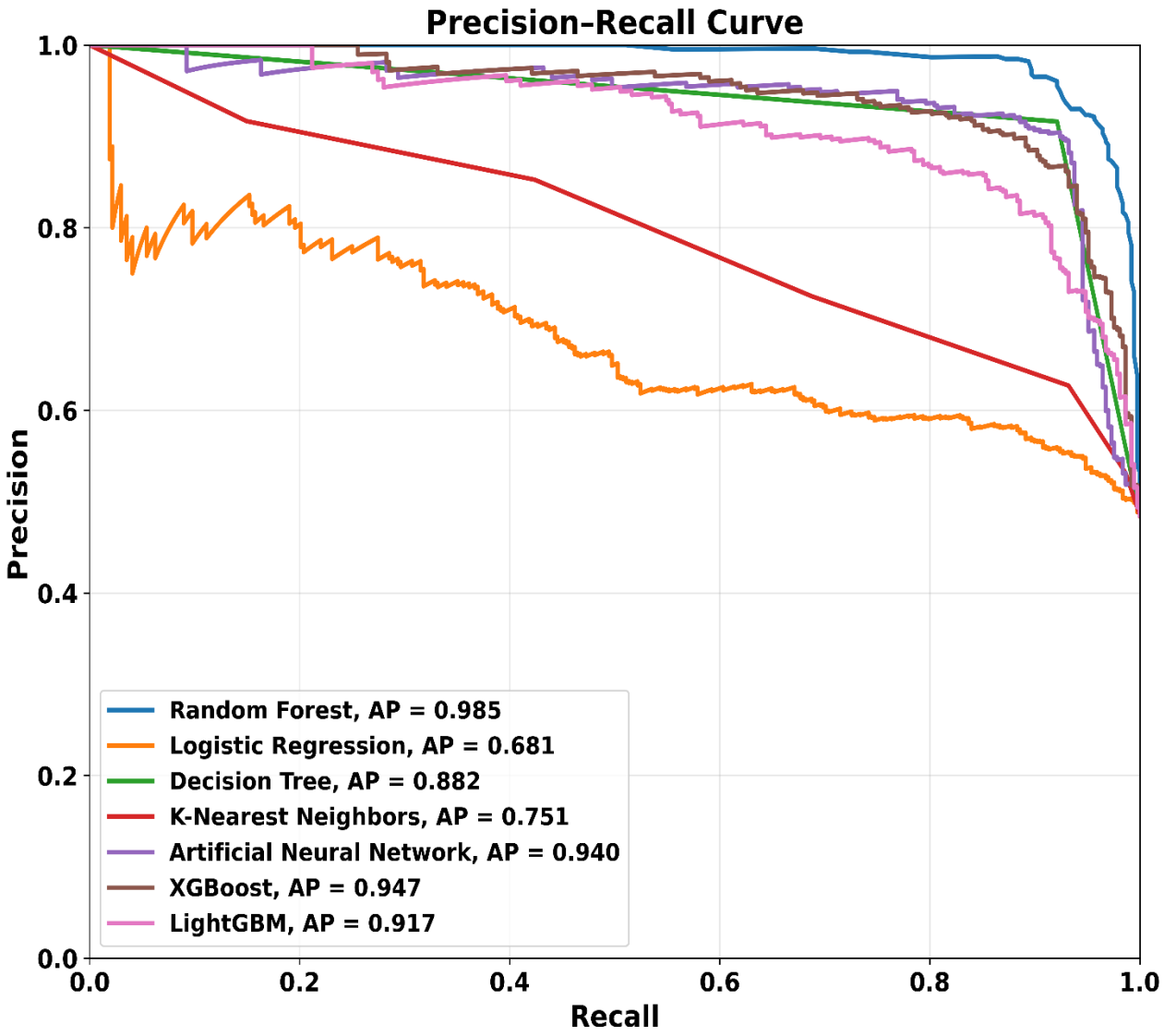


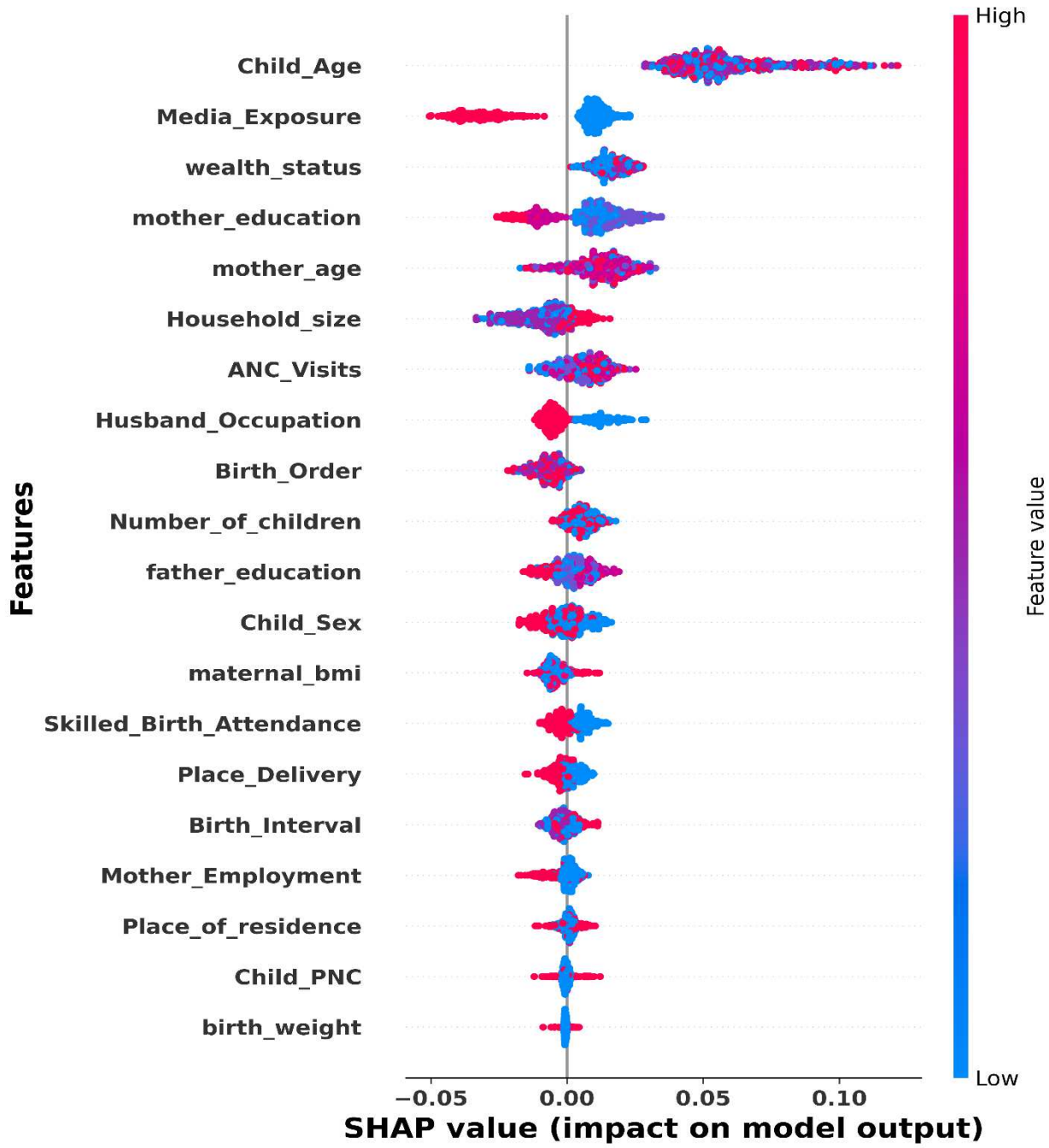
Figure 5 Precision–Recall (PR) curve comparison of machine learning models

SHAP Feature Impact on Model Prediction

SHAP (Shapley Additive Explanations) was applied to the Random Forest model to improve the interpretability of its predictions for severe child food poverty. The analysis was performed on the independent test dataset, allowing the contribution of each predictor to be examined without altering the trained model.

The SHAP analysis showed that child age, wealth index, media exposure, maternal education, household size, maternal age, marital status, and ANC visits were among the important contributors to model predictions. The direction and magnitude of SHAP values indicate whether a particular feature increased or decreased the model's predicted probability of severe child food poverty. However, these values represent model-based predictive contributions and should not be interpreted as causal effects (figure 6)**.**

The SHAP summary plot also demonstrated variation in the influence of predictors across individual children, suggesting that the Random Forest model captured nonlinear relationships and interactions among characteristics**.** Overall, SHAP provided a transparent way to understand how different child, maternal, and household characteristics contributed to the prediction of severe child food poverty and strengthened the interpretability of the final predictive model.



482

483 **Figure 6 SHAP feature impact on model prediction**

484

485

Discussion

This study applied machine learning techniques to predict severe child food poverty among children aged 6–23 months in Ethiopia using data from the 2024-25 Ethiopian Demographic and Health Survey (EDHS). The analysis included 3,792 children and incorporated a range of child, maternal, household, and socioeconomic characteristics. Seven supervised learning algorithms—Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN), Logistic Regression (LR), Artificial Neural Network (ANN), XGBoost, and LightGBM (LGBM)—were developed and compared to determine their ability to distinguish children experiencing severe food poverty from those who were not.

The findings indicate that machine learning approaches can effectively identify patterns associated with severe child food poverty in the Ethiopian context. Among the evaluated algorithms, Random Forest demonstrated the best overall predictive performance, indicating its ability to accommodate complex relationships and interactions between the characteristics included in the analysis. The relatively strong performance of ensemble-based methods such as RF, XGBoost, and LGBM may be attributed to their flexibility in modelling nonlinear relationships that may not be adequately captured by conventional linear approaches.

The predictive analysis further highlighted the importance of several maternal, household, and child-related factors. Maternal education, maternal age, and employment status contributed to the prediction of severe food poverty, while household socioeconomic conditions, particularly wealth status and household size**,** were also influential. Maternal healthcare-related characteristics, including antenatal care utilization**,** contributed to model predictions as well.

Child characteristics, particularly age, were also relevant, reflecting differences in feeding practices and dietary needs during the complementary feeding period.

To improve understanding of the models, explainable machine learning methods were used to examine the contribution of individual predictors. Global feature-importance measures identified variables that contributed most to overall model predictions, while SHAP analysis provided additional information about how individual characteristics influenced predictions for specific observations. This approach helps move beyond prediction alone by providing insight into the factors that drive model outputs.

Nevertheless, these findings should be interpreted within the limitations of the study design. The importance assigned to predictors by machine learning models represents predictive contribution and should not be interpreted as evidence of causality**.** Correlations between variables may also affect feature-importance measures and SHAP values. Furthermore, because the EDHS data are cross-sectional, the observed relationships cannot establish temporal or causal effects.

Child age was significantly associated with severe child food poverty, with children aged 6–11 months being more likely to experience severe food poverty than older children. This finding is consistent with previous research in Ethiopia (6, 33-35),Ghana (36), and Pakistan (37) which reported differences in dietary diversity according to child age, with younger children generally having less diverse diets. The greater vulnerability among younger children may be explained by their transition to complementary feeding, limited exposure to a variety of foods, and greater dependence on caregivers for appropriate feeding (38, 39). Therefore, interventions should prioritize children aged 6–11 months through timely complementary-feeding counselling,

caregiver nutrition education, and improved access to affordable and diverse nutritious foods (40).

Media exposure was significantly associated with severe child food poverty, with children whose mothers had greater exposure to mass media being less likely to experience severe food poverty (41, 42). This may be because regular exposure to radio, television, or other media can improve caregivers' access to information on child nutrition, complementary feeding, and recommended feeding practices (43, 44). Media exposure may also increase awareness of available health and nutrition services and encourage the adoption of appropriate feeding behaviours (45, 46). Previous studies conducted in Ethiopia (47-50), Ghana(51), Mauritania (52), Gambia(53),East Africa(54) and Sub-Saharan African(55) have similarly identified mass-media exposure as an important factor influencing maternal nutrition knowledge and child feeding practices. Therefore, nutrition interventions should strengthen the use of mass media as a channel for targeted nutrition education, particularly to reach caregivers with limited access to conventional health information (56).

Wealth index was significantly associated with severe child food poverty, with children from poorer households having a higher likelihood of experiencing severe food poverty than those from wealthier households, consistent with previous studies in Ethiopia (48, 52, 57), Ghana (36, 58), Mauritania (52), Gambia(53), East Africa(54, 59) ,Sub-Saharan African (60), Pakistan (37)and low- and middle-income countries (61) that have similarly shown that household wealth is an important factor influencing children's access to diverse foods and their risk of inadequate dietary intake. This finding may be explained by the greater likelihood of children in poorer households experiencing limited access to a variety of food groups, as economic disadvantage

550 can restrict the availability and affordability of nutritious foods and increase children's risk of
551 severe child food poverty (62). Moreover, poorer households may be more vulnerable to rising
552 food prices, seasonal food shortages, and limited access to markets, which can further restrict the
553 availability of diverse foods for young children (63, 64). In contrast, children from wealthier
554 households may benefit from greater access to a wider range of foods, better food security,
555 improved access to markets, and greater capacity to provide diverse and nutritious foods (65,
556 66). Therefore, interventions should prioritize children from poorer households through targeted
557 social protection, food-security programs, livelihood support, and improved access to affordable
558 and diverse nutritious foods (67).

559 Maternal education was significantly associated with severe child food poverty in the present
560 study, with children of mothers with lower educational attainment being more likely to
561 experience severe child food poverty, consistent with previous evidence showing that maternal
562 education plays an important role in promoting appropriate child feeding practices, improving
563 dietary intake, and reducing the risk of inadequate nutrition among children (5, 52, 60, 68-70)

564 Higher maternal education may enhance mothers' knowledge of appropriate child feeding
565 practices, improve their ability to make informed food choices, and increase their capacity to
566 access and utilize available resources for child nutrition, thereby potentially reducing the
567 likelihood of severe child food poverty (71).

568 Higher maternal education may improve mothers' knowledge of recommended infant and young
569 child feeding practices, increase their ability to recognize nutritious and locally available foods,
570 and facilitate better use of health and nutrition services (72). Educated mothers may also have

greater decision-making power within the household and improved opportunities to access information through health workers, media, and other sources (73).

Conversely, mothers with limited or no formal education may face greater barriers to obtaining and interpreting nutrition information and may have fewer opportunities to make informed decisions regarding child feeding (74). These disadvantages can contribute to limited dietary variety and inadequate access to diverse foods, thereby increasing the likelihood of severe child food poverty (75).

However, maternal education may also reflect broader socioeconomic conditions, including household wealth, employment, residence, and access to health and nutrition services. Targeted nutrition education and support for mothers with lower educational attainment may therefore help reduce severe child food poverty (73).

In the present study, maternal age was significantly associated with severe child food poverty among children aged 6–23 months. Compared with mothers aged 25–34 years, those younger than 25 years had higher odds of severe child food poverty. This finding is consistent with evidence from Ethiopia (52, 76) South Africa(77), and Sub-Saharan Africa (78), where younger maternal age was associated with poorer dietary diversity and minimum acceptable diets. This may reflect limited feeding experience, reduced access to nutrition information and resources, and competing demands related to education, income, and childcare (79). These findings highlight the need for targeted nutrition counselling and social support for younger mothers during the complementary feeding period (38).

Household size was significantly associated with severe child food poverty in the present study, consistent with previous evidence in Ethiopia (6, 80), Mauritania (81) and Nepal (82) showing that larger household size is associated with poorer child dietary outcomes and increased vulnerability to food poverty. This association may be related to increased competition for limited household food resources, which can reduce the quantity and variety of foods available to young children (83). Larger households may also face greater challenges in meeting the nutritional needs of all members, particularly when food resources are limited (84). Therefore, interventions should prioritize children from larger households through targeted nutrition counselling, food-security support, and strategies to improve access to diverse and nutritious foods (85).

Antenatal care (ANC) visits were significantly associated with severe child food poverty in the present study. This finding is consistent with previous evidence from Ethiopia(6, 86-88), Bangladesh (89) and Pakistan (90),which reported that children whose mothers had fewer than four ANC visits had higher odds of experiencing severe child food poverty. Limited ANC attendance may reduce mothers' opportunities to receive nutrition counselling, breastfeeding guidance, and information on appropriate complementary feeding (91). Regular ANC attendance may therefore improve mothers' knowledge and access to health and nutrition services, potentially reducing the risk of severe child food poverty (92). Strengthening ANC services and integrating nutrition education into routine maternal care may help improve children's dietary intake (38).

Overall, this study demonstrates that machine learning can provide a useful approach for predicting severe child food poverty among children aged 6–23 months in Ethiopia. The Random

Forest model showed the strongest predictive performance among the evaluated algorithms, while explainable machine learning helped identify the characteristics that contributed most to model predictions**.** Child age, maternal age, maternal education, media exposure, wealth index, household size, and ANC utilization emerged as important predictive factors, highlighting the multifaceted nature of severe child food poverty. These findings suggest that efforts to reduce severe child food poverty should not focus solely on household economic conditions but should also consider maternal characteristics, access to health and nutrition information, and household circumstances. Integrating nutrition counselling into maternal health services, strengthening nutrition communication through mass media, improving access to diverse and affordable foods, and prioritizing economically vulnerable and larger households may help reduce the burden of severe child food poverty in Ethiopia. The use of explainable machine learning further provides an opportunity to identify high-risk children and support more targeted nutrition interventions and resource allocation.

Conclusion and Recommendations

Severe child food poverty affected 46.94% of children aged 6–23 months in this study, highlighting a substantial nutritional challenge in Ethiopia. Random Forest showed the best predictive performance**,** while explainable machine learning identified child age, maternal age, education, marital status, media exposure, household wealth, household size, and ANC utilization **a**s important predictors. These findings demonstrate the potential of machine learning to identify children at greater risk and support targeted nutrition interventions.

Nutrition interventions should prioritize younger children, younger and less-educated mothers, poorer and larger households**,** with strengthened complementary-feeding counselling and nutrition education. ANC and mass media should be used to improve access to child-feeding

information, while social protection and food-security programs should support economically vulnerable households. Further studies should validate the models using recent and longitudinal data to improve their applicability for targeted nutrition programs.

Strengths and Limitations of study

A major strength of this study is the use of the recent 2024–25 EDHS data, providing up-to-date evidence on severe child food poverty in Ethiopia. The study also compared seven machine learning algorithms—Random Forest, Decision Tree, KNN, Logistic Regression, ANN, XGBoost, and LightGBM—to identify the model with the strongest predictive performance. In addition, the use of explainable machine learning techniques, including feature importance and SHAP analysis, improved the interpretation of model predictions and helped identify important predictors of severe child food poverty.

The study has some limitations. First, the cross-sectional nature of the EDHS data limits the ability to establish causal or temporal relationships between the identified predictors and severe child food poverty. Second, dietary information was based on food consumption during the previous 24 hours, which may be subject to recall or reporting errors. Third, although the models showed good predictive performance, their performance may vary when applied to other populations or settings. Finally, feature importance and SHAP values represent predictive contributions rather than causal effects and may be influenced by correlations among predictors. Therefore, the findings should be interpreted primarily in a predictive context.

Abbreviations

ANC: Antenatal Care

ANN: Artificial Neural Network

CI: Confidence Interval

DHS: Demographic and Health Survey

DT: Decision Tree

EDHS: Ethiopia Demographic and Health Survey

F1: F1-score

KNN: K-Nearest Neighbors

LR: Logistic Regression

MDD: Minimum Dietary Diversity

ML: Machine Learning

PR-AUC: Precision–Recall Area Under the Curve

RF: Random Forest

ROC-AUC: Receiver Operating Characteristic Area Under the Curve

SMOTE: Synthetic Minority Over-sampling Technique

XGBoost: Extreme Gradient Boosting

Declarations

Ethical approval and consent to participate

The study was based on publicly available data from the Demographic and Health Surveys (DHS) Program. Permission to access and use the datasets was obtained from the DHS Program website (http://www.dhsprogram.com) after submitting a brief study description. Ethical

approval for DHS data collection was obtained by the DHS Program from the ICF Institutional Review Board (IRB) and from the national ethics review committees of each participating country. The surveys were conducted in accordance with relevant guidelines and regulations. Informed consent was obtained from all participants by the DHS Program prior to data collection. The datasets were anonymized, and no personal identifiers were used in this secondary analysis. No additional ethical approval was required for this study.

Data Availability Statement

The data used in this study are publicly available from the Demographic and Health Surveys (DHS) Program. Access to the datasets can be obtained by registered users through the DHS Program website (http://www.dhsprogram.com) upon reasonable request and approval of a brief study description.

Funding

Not applicable

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

Consent for publication

Not applicable

Competing Interests

All authors declared that they have no any competing interest.

Clinical trial number: not applicable.

Authors' contribution

SFT was responsible for conceptualization, design, data extraction, formal analysis, language editing, data interpretation, methodology, funding acquisition, project administration, resource management, software development, supervision, data curation, article review, validation, visualization, and writing the original draft as well as reviewing and editing.

DKA,DEA,MEZ,AEA,BAM,HNA,KYW,TAA,ABG,JMK,HAK,AKM,AEG,TCM,FBK,and MFT contributed to data curation, conceptualization, formal analysis, and funding acquisition. They reviewed the study design and draft manuscript, verified the analysis, and made significant contributions through critical revision and article review. All authors approved the final version of the manuscript

Acknowledgments

We would like to express our gratitude to the DHS Program for granting permission for this study in accordance with research ethics.

References

1. Fund UNCs. Child Food Poverty: Nutrition Deprivation in Early Childhood. New York,NY: UNICEF, 2024 June 2024. Report No.
2. Grosso G, Mateo A, Rangelov N, Buzeti T, Birt C. Nutrition in the context of the Sustainable Development Goals. European journal of public health. 2020;30(Supplement_1):i19-i23.
3. World Health Organization. Child feeding: minimum dietary diversity, 6–23 months Geneva: World Health Organization. Available from: https://www.who.int/data/gho/indicator-metadata-registry/imr-details/7042.
4. Quadra MR, Meller FO, Schäfer AA, Santos LP, Dalpont AD, Espíndola GE, et al. Food Poverty and Early Childhood Development Across Food Insecurity Levels in Brazil. Maternal & Child Nutrition. 2026;22(3):e70198.

5. Belay A, Noor R, Tessema B, Woldeyohannes M, Tefera N, Girma M, et al. Prevalence and Drivers of Child Food Poverty in Ethiopia: Evidence From a Nationally Representative Survey. Matern Child Nutr. 2026;22(2):e70186.
6. Yemane Z, Kare AP, Bolka A, Feleke FW. Child food poverty prevalence and its associated factors in Dale district, Sidama region, Ethiopia. PLOS ONE. 2025;20(7):e0326999.
7. Solomon D, Aderaw Z, Tegegne TK. Minimum dietary diversity and associated factors among children aged 6–23 months in Addis Ababa, Ethiopia. International journal for equity in health. 2017;16(1):181.
8. Belay A, Noor R, Ba T, Woldeyohannes M, Tefera N, Girma M, et al. Prevalence and Drivers of Child Food Poverty in Ethiopia: Evidence From a Nationally Representative Survey. Maternal & Child Nutrition. 2026;22.
9. Cusick SE, Georgieff MK. The Role of Nutrition in Brain Development: The Golden Opportunity of the "First 1000 Days". J Pediatr. 2016;175:16-21.
10. Ahmad A, Madanijah S. Complementary feeding practices and nutritional status of children 6-23 months old: formative study in Aceh, Indonesia. 2018;12(6):512-20.
11. Dewey KG, Brown KH. Update on technical issues concerning complementary feeding of young children in developing countries and implications for intervention programs. Food Nutr Bull. 2003;24(1):5-28.
12. De Sanctis V, Soliman A, Alaaraj N, Ahmed S, Alyafei F, Hamed N. Early and Long-term Consequences of Nutritional Stunting: From Childhood to Adulthood. Acta Biomed. 2021;92(1):e2021168.
13. Kar BR, Rao SL, Chandramouli B. Cognitive development in children with chronic protein energy malnutrition. Behavioral and Brain Functions. 2008;4(1):31.
14. Elegbeleye JA, Fayemi OE, Agbemavor WSK, Krishnamoorthy S, Adebowale OJ, Adeyanju AA, et al. Beyond Calories: Addressing Micronutrient Deficiencies in the World's Most Vulnerable Communities—A Review. Nutrients. 2025;17(24):3960.
15. Black RE, Allen LH, Bhutta ZA, Caulfield LE, De Onis M, Ezzati M, et al. Maternal and child undernutrition: global and regional exposures and health consequences. The lancet. 2008;371(9608):243-60.
16. Black R. Micronutrient deficiency: an underlying cause of morbidity and mortality. SciELO Public Health; 2003. p. 79-.
17. Khamis AG, Mwanri AW, Ntwenya JE, Kreppel K. The influence of dietary diversity on the nutritional status of children between 6 and 23 months of age in Tanzania. BMC Pediatr. 2019;19(1):518.
18. Mulatu S, Mekonnen GB, Tsehay YT, Mamo ST, Messelu MA, Belay AE, et al. Dietary diversity and associated factors among children 6–23 months old in Ethiopia: systematic review and Meta-Analysis. Discov Med. 2024;36(186):1527-43.
19. Choudhury S, Headey DD, Masters WA. First foods: Diet quality among infants aged 6–23 months in 42 countries. Food policy. 2019;88:101762.
20. Tizazu W, Laillou A, Hirvonen K, Chitekwe S, Baye K. Child feeding practices in rural Ethiopia show increasing consumption of unhealthy foods. Maternal & Child Nutrition. 2024;20:e13401.
21. Omar MA, Mouse AI, Ahmed HA, Shidane HM, Muse AH. Spatial Patterns and Multilevel Determinants of Minimum Dietary Diversity Among Children Aged 6–23 Months

in Somaliland: Evidence from a National Survey. Clinical Nutrition Open Science. 2026:100644.
22. Bain LE, Awah PK, Geraldine N, Kindong NP, Siga Y, Bernard N, et al. Malnutrition in Sub–Saharan Africa: burden, causes and prospects. Pan African Medical Journal. 2013;15(1).
23. Amoako M, Oguah R, Mensah C, Essiam FAAP, Martyn-Dickens C, Hamzah DS, et al. The impact of climate variables on nutritional status of children 0-6 Years old In Africa-A systematic review. Heliyon. 2026;12(7).
24. Demmler KM, Tutwiler MA. Diet, nutrition, and climate: historical and contemporary connections. Frontiers in Nutrition. 2024;11:1516968.
25. UNICEF. Child food poverty: nutrition deprivation in early childhood. 2024.
26. Unicef. Prospects for Children in 2022. 2022.
27. Croft T, Allen CK, Zachary BW, Arnold F, Assaf S, Balian S. Guide to DHS statistics DHS-8. Rockville, Maryland, USA: ICF. 2023.
28. Rajan A. Data Cleaning for Machine Learning Systems-A Survey. 2024.
29. Dhawas P, Dhore A, Bhagat D, Pawar RD, Kukade A, Kalbande K. Big data preprocessing, techniques, integration, transformation, normalisation, cleaning, discretization, and binning. Big Data Analytics Techniques for Market Intelligence: IGI Global Scientific Publishing; 2024. p. 159-82.
30. Cheng X. A comprehensive study of feature selection techniques in machine learning models. Available at SSRN 5154947. 2024.
31. Brownlee J. Recursive feature elimination (RFE) for feature selection in Python. Machine Learning Mastery. 2020;25.
32. Wongvorachan T, He S, Bulut O. A comparison of undersampling, oversampling, and SMOTE methods for dealing with imbalanced classification in educational data mining. Information. 2023;14(1):54.
33. Anato A. Severe acute malnutrition and associated factors among children under-five years: A community based-cross sectional study in Ethiopia. Heliyon. 2022;8(10):e10791.
34. Fufa DA, Laloto TD. Factors associated with undernutrition among children aged between 6–36 months in Semien Bench district, Ethiopia. Heliyon. 2021;7(5):e07072.
35. Ahmed JA, Sadeta KK, Lenbo KH. Magnitude and factors associated with appropriate complementary feeding practice among mothers of children 6–23 months age in Shashemene town, Oromia-Ethiopia: Community based cross sectional study. PloS one. 2022;17(3):e0265716.
36. Inusah A-W, Nwuzoh MI, Mogre V, Ziblim S-D. Trends in severe and moderate child food poverty among children aged 6-23 months in Ghana, 2008-2022. PAMJ Clinical Medicine. 2026;54(62).
37. Kumar R, Mahmood T, Naeem N, Khan SA, Hanif M, Pongpanich S. Minimum dietary diversity and associated determinants among children aged 6–23 months in Pakistan. Scientific Reports. 2024;14(1):2639.
38. Organization WH. WHO Guideline for complementary feeding of infants and young children 6-23 months of age: World Health Organization; 2023.
39. Stiller CK, Golembiewski SKE, Golembiewski M, Mondal S, Biesalski HK, Scherbaum V. Maternal nutritional status and child feeding practices: a retrospective study in Santal

communities, Birbhum District, West Bengal, India. International Breastfeeding Journal. 2020;15(1):50.
40. Birhanu S, Alene GD, Demilew YM. Appropriate complementary feeding practices and associated factors among mothers with infants aged 6–8 months in West Gojjam Zone, Northwest Ethiopia: A mixed methods study. PLoS One. 2025;20(10):e0334740.
41. Kerins C, Furey S, Kerrigan P, McCartan A, Kelly C, Vaughan E. News media framing of food poverty and insecurity in high-income countries: a rapid review. Health Promotion International. 2023;38(6):daad188.
42. Jung S, Lee H-Y, Choe S-a, Oh H, Subramanian SV, Kim R. Maternal media exposure and child anthropometric failures across 40 low- and middle-income countries. SSM - Population Health. 2025;29:101746.
43. Makwela MS, Mashaba RG. Determinants of sub-optimal complementary feeding practices among caregivers of children aged 6-23 months in low-and middle-income countries: scoping review. Front Public Health. 2025;13:1655685.
44. Dhawan D, Pinnamaneni R, Viswanath K. Association between mass media exposure and infant and young child feeding practices in India: a cross-sectional study. Scientific Reports. 2023;13(1):19353.
45. Dhawan D, Pinnamaneni R, Viswanath K. Association between mass media exposure and infant and young child feeding practices in India: a cross-sectional study. Scientific Reports. 2023;13.
46. Çakır MA, Fırat S. Eating behaviors in the digital age: the role of social media and healthy diet literacy. Eating and Weight Disorders - Studies on Anorexia, Bulimia and Obesity. 2026;31(1):13.
47. Gonete KA, Angaw DA, Gezie LD. Minimum acceptable diet and associated factors among children aged 6–23 months in Ethiopia: a systematic review and meta-analysis. BMC pediatrics. 2024;24(1):151.
48. Teshome F, Tadele A. Trends and determinants of minimum acceptable diet intake among infant and young children aged 6–23 months in Ethiopia: a multilevel analysis of Ethiopian demographic and health survey. BMC nutrition. 2022;8(1):44.
49. GETU TA. COMPLEMENTARY FEEDING PRACTICE AND ASSOCIATED FACTORS AMONG MOTHERS HAVING CHILDREN 6–23 MONTHS OF AGE, EAST BELESA DISTRICT, NORTHEAST ETHIOPIA 2022.
50. Amente T, Kebede Y, Belachew T. Social-demographic and behavioral predictors of core indicators of complementary feeding practices among mothers of children aged 6–23 months: baseline results from a cluster-randomized trial in rural Ethiopia. BMC pediatrics. 2025;25(1):517.
51. Appiah B, Saaka M, Appiah G, Asamoah-Akuoko L, Samman E, Forastiere L, et al. The association between exposure to a radio campaign on nutrition and mothers' nutrition-and health-related attitudes and minimal acceptable diet of children 6–36 months old: a quasi-experimental trial. Public Health Nutrition. 2024;27(1):e232.
52. Belay A, Noor R, Tessema B, Woldeyohannes M, Tefera N, Girma M, et al. Prevalence and Drivers of Child Food Poverty in Ethiopia: Evidence From a Nationally Representative Survey. Maternal & Child Nutrition. 2026;22(2):e70186.
53. Terefe B, Jembere MM, Assimamaw NT. The prevalence and multilevel analysis of minimum dietary diversity intake and its determinants among 6–23 months old infants in

The Gambia: further analysis of the Gambian demographic and health survey data. Journal of Health, Population and Nutrition. 2023;42(1):98.
54. Worku MG, Alamneh TS, Tesema GA, Alem AZ, Tessema ZT, Liyew AM, et al. Minimum acceptable diet feeding practice and associated factors among children aged 6–23 months in east Africa: a multilevel binary logistic regression analysis of 2008–2018 demographic health survey data. Archives of public health. 2022;80(1):127.
55. Mekonen EG, Zegeye AF, Workneh BS. Complementary feeding practices and associated factors among mothers of children aged 6 to 23 months in Sub-saharan African countries: a multilevel analysis of the recent demographic and health survey. BMC Public Health. 2024;24(1):115.
56. Saaka M, Wemah K, Kizito F, Hoeschle-Zeledon I. Effect of nutrition behaviour change communication delivered through radio on mothers' nutritional knowledge, child feeding practices and growth. Journal of nutritional science. 2021;10:e44.
57. Belay A, Noor R, Tessema B, woldeyohannes M, Tefera N, Girma M, et al. Prevalence and Drivers of Child Food Poverty in Ethiopia: Evidence From a Nationally Representative Survey. Maternal & Child Nutrition. 2026;22(2):e70186.
58. Atosona A, Mohammed JA, Issahaku H, Saani K, Addae HY, Azupogo F. Maternal employment status and child age are positive determinants of minimum dietary diversity among children aged 6–23 months in Sagnarigu municipality, Ghana: a cross-sectional study. BMC nutrition. 2024;10(1):57.
59. Raru TB, Merga BT, Mulatu G, Deressa A, Birhanu A, Negash B, et al. Minimum dietary diversity among children aged 6–59 months in East Africa countries: a multilevel analysis. International journal of public health. 2023;68:1605807.
60. Paulo HA, Andrew J, Luoga P, Omary H, Chombo S, Mbishi JV, et al. Minimum dietary diversity behaviour among children aged 6 to 24 months and their determinants: insights from 31 Sub-Saharan African (SSA) countries. BMC nutrition. 2024;10(1):160.
61. Birhanu F, Yitbarek K, Bobo FT, Atlantis E, Woldie M. Undernutrition in children under five associated with wealth-related inequality in 24 low- and middle-income countries from 2017 to 2022. Scientific Reports. 2024;14(1):3326.
62. Marino D, Bernaschi D, Felici FB, Scannavacca F, Minotti B. Measuring local poverty and food insecurity: Developing an affordability index for healthy diets. Regional Science Policy & Practice. 2025;17(12):100244.
63. Mutandani V, Subramani T, Kalirajan M, Manalil S. Systematic review for seasonal crop diversity influence on the double burden of malnutrition in rural communities. Frontiers in Sustainable Food Systems. 2025;Volume 9 - 2025.
64. Roba K, O'Connor T, O'Brien N, Aweke C, A. Kahsay Z, Chisholm N, et al. Seasonal variations in household food insecurity and dietary diversity and their association with maternal and child nutritional status in rural Ethiopia. Food Security. 2019;11:651-64.
65. Niazi R, Liu A, Han J, Hassan S, Elham H, Osewe M. Household Income Diversification and Food Insecurity: A Case Study of Afghanistan. Foods. 2025;14(12):2048.
66. Nandi R, Nedumaran S, Ravula P. The interplay between food market access and farm household dietary diversity in low and middle income countries: A systematic review of literature. Global Food Security. 2021;28:100484.
67. Kunlere A. Strategies to address food insecurity and improve global nutrition among at-risk populations. International Journal of Science and Research Archive. 2025;14:1657-80.

68. Seyoum A, Tsegaye A, Samuel A, Amede T. Factors influencing under five children dietary diversity score: a cross-sectional study in enset-based farming systems of Sidama Regional State, Ethiopia. J Human Nutr Food Sci. 2024;12(1):10.47739.
69. Rezaeizadeh G, Mansournia MA, Keshtkar A, Farahani Z, Zarepour F, Sharafkhah M, et al. Maternal education and its influence on child growth and nutritional status during the first two years of life: a systematic review and meta-analysis. EClinicalMedicine. 2024;71:102574.
70. Assfaw MA, Tesfaye D, Fenta HM, Zewdia WF, Muchie BT, Asmelash D. Predictors of inadequate minimum acceptable diet among infants and young children in Ethiopia: a multilevel logistic regression analysis. Front Public Health. 2025;13:1464008.
71. Nguyen-Phung HT, Yu Y, Nguyen PH, Le H. Maternal Education and Child Development: Insights From Nutritional Status in Kenya. Health Economics. 2026;35(5):778-95.
72. Rotella R, Soriano JM, Peraita-Costa I, Llopis-González A, Morales-Suarez-Varela M. Maternal Education and Its Association with Dietary Diversity and Pregnancy and Breastfeeding Practices in Rural Madagascar. Women [Internet]. 2026; 6(1):[13 p.].
73. Paul S, Paul S, Gupta AK, James KS. Maternal education, health care system and child health: Evidence from India. Social Science & Medicine. 2022;296:114740.
74. Bimpong KA, Cheyuo EK, Abdul-Mumin A, Ayanore MA, Kubuga CK, Mogre V. Mothers' knowledge and attitudes regarding child feeding recommendations, complementary feeding practices and determinants of adequate diet. 2020;6(1):67.
75. Mastan M, Rajan S, Sawant R, Pantvaidya S, D'Souza V, Das S. Association between maternal and child minimum dietary diversity in urban informal settlements: evidence from a cross-sectional study in Mumbai, India. BMC nutrition. 2025;11(1):217.
76. Birhanu F, Yitbarek K, Atlantis E, Woldie M, Bobo F. Trends in social determinants of inequality in child undernutrition from the Ethiopian Demographic and Health Surveys, 2005–2016. PLoS One. 2024;19(1):e0295810.
77. Mathosi MM, Cele LP, Mathibe M, Modjadji P. Acute malnutrition in under-five children in KwaZulu-Natal, South Africa: Risk factors and implications for dietary quality. Nutrients. 2025;17(12):2038.
78. Hailu BA, Daba C, Tsega Y, Asaminew A, Miheretu BA, Endawkie A. Geospatial distribution and multilevel determinants of inadequate minimum dietary diversity and its consequences for children aged 6–23 months in Sub-Saharan Africa. Plos one. 2025;20(5):e0321254.
79. Mundagowa PT, Keseko E, Musungu R, Tembo P, Chiyaka ET, Dzinamarira T, et al. Experiences, barriers, and enablers of infant and young child feeding among adolescent mothers in Sub-Saharan Africa: a scoping review protocol. Systematic Reviews. 2025;15(1):34.
80. Tafese Z, Reta F, Mulugeta B, Anato A. Child undernutrition and associated factors among children 6–23 months old in largely food insecure areas of rural Ethiopia. Journal of Nutritional Science. 2022;11:e63.
81. Asebe HA, Eshun G, Andargie BA. Dietary diversity and its associated factors among children aged 6-23 months in mauritania: evidence from national survey. BMC nutrition. 2025;11(1):148.

82. Ghimire U, Aryal BK, Gupta AK, Sapkota S. Severe acute malnutrition and its associated factors among children under-five years: a facility-based cross-sectional study. BMC pediatrics. 2020;20(1):249.
83. Fikadu K, Yihune M, Boynito WG, Hailemariam Z. Exploring multiple barriers to proper child feeding practices in rural districts of Ethiopia. Food science & nutrition. 2025;13(3):e4757.
84. Betterdel AN, Meriki HD, Mbanga CM, Nzefa LD, Nchung AJ, Mbhenyane XG, et al. Poor dietary diversity, a key determinant of household food insecurity: insights from a community-based survey in Buea health district, Cameroon. Journal of Hunger & Environmental Nutrition. 2024;19(6):966-84.
85. Ayele K, Demisew M, Gemede HF. A systematic review of the impact of food and nutrition programs on child nutrition and household food security in Ethiopia. BMC nutrition. 2025;11(1):214.
86. Belay A, Noor R, Tessema B, Woldeyohannes M. Prevalence and Drivers of Child Food Poverty in Ethiopia: Evidence From a Nationally Representative Survey. 2026;22(2):e70186.
87. Tafese Z, Reta F, Mulugeta B, Anato A. Child undernutrition and associated factors among children 6-23 months old in largely food insecure areas of rural Ethiopia. 2022;11:e63.
88. Sisay BG, Afework T, Jima BR, Gebru NW, Zebene A, Hassen HY. Dietary diversity and its determinants among children aged 6–23 months in Ethiopia: evidence from the 2016 demographic and health survey. Journal of Nutritional Science. 2022;11:e88.
89. Rifat M, Islam R, Didar RB, Bhowmick J, Sarkar P, Amin MR, et al. Effects of maternal use of the continuum of care on complementary feeding practices in Bangladesh: cross-sectional study. JMIR Public Health and Surveillance. 2025;11:e76666.
90. Baxter JAB, Wasan Y, Islam M, Cousens S, Soofi SB, Ahmed I, et al. Dietary diversity and social determinants of nutrition among late adolescent girls in rural Pakistan. Maternal & child nutrition. 2022;18(1):e13265.
91. Roba AA, Tola A, Dugassa D, Tefera M, Gure T, Worku T, et al. Antenatal care utilization and nutrition counseling are strongly associated with infant and young child feeding knowledge among rural/semi-urban women in Harari region, Eastern Ethiopia. Frontiers in pediatrics. 2022;10:1013051.
92. Zeleke EA, AN TH. Food Insecurity Associated with Attendance to Antenatal Care Among Pregnant Women: Findings from a Community-Based Cross-Sectional Study in Southern Ethiopia. 2020;13:1415-26.