One Decade of Artificial Intelligence (AI) Research in Public Health Stunting Prediction and Intervention

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Abstract—**Stunting attributable to malnutrition remains a global public health problem impacting the long-term physical and cognitive growth of children. In recent years, artificial intelligence (AI) has been applied in public health research to help diagnose and predict stunting. This study seeks to review trends in AI research on stunting prediction and intervention, and to identify existing challenges and opportunities. The articles were screened using the Systematic Literature Review (SLR) method with the PRISMA protocol through databases like PubMed, ScienceDirect, Scopus, and Google Scholar. The analysis of the data was performed using VOSviewer and Microsoft Excel. The results showed that the most used models in predicting stunting were Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting (XGBoost, LGBM), and Artificial Neural Network (ANN). Model evaluation is usually done through metrics such as AUC-ROC, accuracy, sensitivity, and specificity. Although AI has shown promise in identifying and predicting stunting, a few challenges remain: One is of data access and quality; others are model interpretability and integration within healthcare networks. Towards increasingly promising application outcomes: future directions for home-based health data prediction of the Internet of Things (IoT), Explainable AI (XAI), Multimodal AI, and natural language processing (NLP) models.**

Keywords—Artificial intelligence; stunting; public health; machine learning; systematic review

I. Introduction

Malnutrition results from an energy or nutrient intake that does not meet the body's needs [1] . This condition includes imbalance, deficiency, excess, and overall energy and nutrient imbalance. The main forms of malnutrition include undernutrition (stunting and wasting), obesity, and micronutrient deficiencies such as vitamin A, iron, and iodine. Malnutrition remains a major public health problem affecting individuals across all age groups and contributes to various health, social, and psychological issues. It is estimated that up to 20 million children experience stunted growth and reduced life expectancy due to undernutrition, which also remains a significant cause of infant mortality [2].

According to the World Health Organization (WHO), malnutrition encompasses both undernutrition and overnutrition conditions, including overweight and obesity [3]. Global projections indicate that nutritional challenges will remain significant, with an estimated 127 million children (26%) still affected by stunting by 2025. Although the WHO has set a target to reduce stunting among children under five by 40%, current progress suggests that this goal may not be fully achieved. Addressing malnutrition is also a key priority in the United Nations Sustainable Development Goals (SDGs), particularly Goal 2 (Zero Hunger), which aims to eliminate all forms of malnutrition by 2030.

Advancements in computing technology have introduced new opportunities to address public health challenges. Traditionally, stunting has been analyzed using classical statistical methods; however, these approaches face limitations such as multicollinearity among variables, which can reduce diagnostic accuracy. Artificial Intelligence (AI) offers advantages in overcoming these limitations and has demonstrated improved performance in classification tasks, including stunting detection [4]. Therefore, the application of AI in public health has become increasingly important for improving early detection and intervention strategies.

This study provides several key contributions to the existing literature. First, it presents a comprehensive ten-year analysis of AI applications in stunting prediction and intervention, highlighting temporal research trends and methodological evolution. Second, it offers a detailed geographical analysis of research distribution, emphasizing the dominance of developing countries and their implications for model generalizability. Third, this study identifies research gaps in underexplored areas such as malnutrition diagnosis, real-time data utilization, and explainable AI. Finally, it provides a critical synthesis of commonly used AI models, including their strengths, limitations, and suitability for different types of health data.

II. Literature Review

Artificial Intelligence (AI) refers to computational systems capable of performing tasks that typically require human intelligence, including data collection, pattern recognition, prediction, and decision-making [5][6]. The development of AI has evolved from symbolic AI, which relied on predefined rules, to modern AI approaches that can learn from data [7][8]. While symbolic AI was effective for structured problems, it was limited in handling complex and unstructured data such as images, speech, and text.

Machine Learning (ML), a subset of AI, enables systems to learn from data without explicit programming by identifying patterns within labeled datasets [9]. Deep Learning (DL), an advanced form of ML, utilizes multi-layered neural networks to capture complex patterns and relationships in large-scale and unstructured data [10]. Compared to traditional ML methods, DL provides higher capability in modeling complex data structures, particularly in domains such as image classification and health data analysis.

Several studies have applied ML and DL techniques to address malnutrition and stunting. Previous research shows that deep learning models can achieve high performance, with accuracy reaching 96.46% and AUC-ROC up to 99.95% [11]. In Afghanistan, algorithms such as J48, Random Forest (RF), and Naïve Bayes have been used to detect edematous malnutrition, with RF achieving the highest accuracy of 97.14% [12]. Similarly, Artificial Neural Networks (ANNs) have been applied in Bangladesh to classify children's nutritional status, demonstrating strong performance and potential as decision-support tools for policymakers [13].

Other machine learning approaches, such as K-Nearest Neighbors (K-NN), have been used to detect stunting based on anthropometric indicators [14]. Comparative studies using algorithms like XGBoost (XGB), Naïve Bayes (NB), Random Forest (RF), and Logistic Regression (LR) have also been conducted using demographic health survey datasets to evaluate predictive performance.

Stunting, as a long-term consequence of malnutrition, can lead to significant physical and cognitive impairments. Research using generalized linear mixed models on Ethiopian Demographic Health Survey data identified age as a significant risk factor, with children aged 12–59 months showing a higher risk compared to younger age groups [15]. These findings highlight the importance of early intervention in reducing stunting prevalence.

Recent developments have also introduced AI-based decision support systems for the early detection of malnutrition risk. One study utilized mobile health (m-Health) data and applied various ML models combined with techniques such as Synthetic Minority Oversampling Technique (SMOTE) and cost-sensitive learning. The results showed high performance, with accuracy reaching 94% and recall of 92%, indicating strong potential for AI in supporting public health policies [16].

In addition, several literature reviews have explored the application of AI in public health. However, many studies focus on general AI applications rather than specifically addressing stunting. Therefore, a systematic literature review is necessary to identify research trends, gaps, and opportunities in AI-based stunting prediction and intervention. This study adopts the PRISMA protocol and utilizes databases such as PubMed, ScienceDirect, Scopus, and Google Scholar. Data analysis is conducted using tools such as Microsoft Excel and VOSviewer to examine research trends, locations, methodologies, and study topics.

III. Materials and Methods

The method used for this research is the Systematic Literature Review (SLR). The main goal of this content is to review the literature regarding the application of artificial intelligence in the health area, specifically related to stunting, as well as to summarize previous studies and present new contributions with the potential to lead to advances in this field. This leads to the following research questions that further define these objectives:

- RQ1: How have public health applications related to stunting used AI methods (over the past decade, worth researching trends, AI methodologies, and their implementations)?
- RQ2: How well do artificial intelligence models (such as algorithms used, accuracy assessment, and model reliability) predict stunting status based on the types of data sources used?
- RQ3: What challenges and opportunities exist for the development and application of artificial intelligence (including research limitations, implementation challenges, and recommendations on future development) to aid the early detection and intervention of stunting within communities, and what solutions do current trends in research offer?

A. Search Strategy

Ms. Excel and VOSviewer software were utilized to analyze data from this study and provide an adequate results overview. The data collection was done under the PRISMA workflow (Fig. 1): identification, abstract screening, manuscript eligibility assessment, and article selection, in four steps. In the identifying stage, a search was done through different database sources to ensure a wide data range and to recognize relevant studies. [17]. Data Sources: The following are the sources for this literature database: ScienceDirect ("www. sciencedirect. com," last accessed Dec. 31, 2024), PubMed ("pubmed. ncbi. nlm. nih. (https://www.scopus.com), and Google Scholar http://scholar.google.com (accessed December 11, 2024).

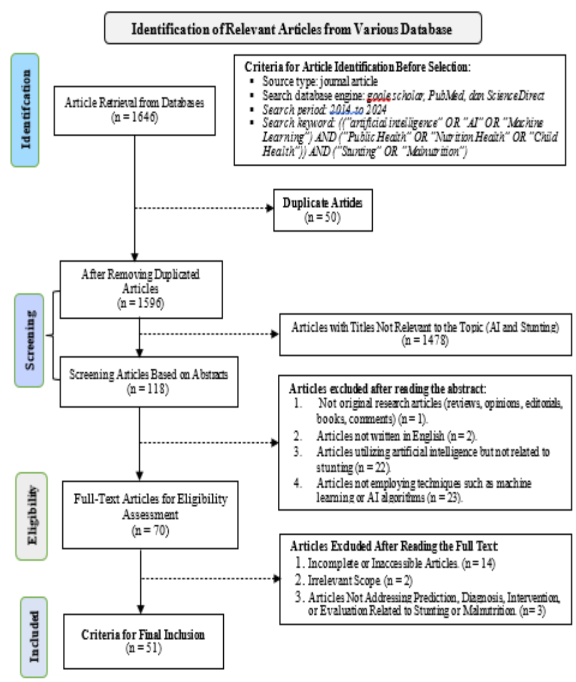

Fig. 1. PRISMA flow diagram.

Articles were downloaded from their websites from 2015 to 2024. Automated searches using Boolean techniques were conducted to connect keywords, generating summaries shown in Table I.

TABLE I. KEYWORDS AND NUMBER OF ARTICLES

Keyword	Database Source	Count
((“artificial intelligence” OR “AI” OR “Machine Learning”) AND (“Public Health” OR “Nutrition Health” OR “Child Health”)) AND (“Stunting” OR “Malnutrition”	ScienceDirect	363
	PubMed	234
	Google Scholar	1000
	Scopus	49
Total Count		**1646**

B. Inclusion and Exclusion Criteria

Ms. Excel was employed to perform a preliminary screening of the manuscripts. In this process, duplicate articles were eliminated, resulting in a total of 1,596 articles compared to the 1,646 obtained in the identification step. Then, articles were screened based on titles, only retaining articles relevant to the topics of AI and stunting (a total of 118 articles). Making sure to apply our inclusion/exclusion criteria, the next step was searching the articles by title/abstract. The inclusion criteria applied for selecting articles are presented in the following Table II.

TABLE II. INCLUSION AND EXCLUSION CRITERIA

Inclusion	Exclusion
Articles published in the last 10 years, from 2015 to 2024.	Post 2015 or pre 2024 articles.
Articles written in English	Articles that are not in English.
Studies taken using AI techniques, e.g., machine learning, deep learning, or neural networks.	Non-AI/non-computational technique studies.
Reported on prediction, diagnosis, intervention, or evaluation of stunting or malnutrition	Reasons: Articles with no direct relevance to stunting, malnutrition, or child nutrition.
Research articles (empirical studies, systematic and meta-analyses).	Non-peer-ended content (eg, editorials, opinion articles, book chapters, conference abstracts).

C. Data Extraction and Thematic Synthesis

This search yielded 70 full-text articles. The eligibility of records was evaluated in the fourth stage by reading all the full-text articles and choosing them according to the specified inclusion and exclusion criteria. A total of 51 eligible articles were identified for the review. A detailed literature mapping was undertaken from the 51 selected articles, including details such as the article title, year of publication, authors, research objectives, research location, methodology, data sources, research scope, data analytics techniques used, key findings, and journal indexing (Fig. 2).

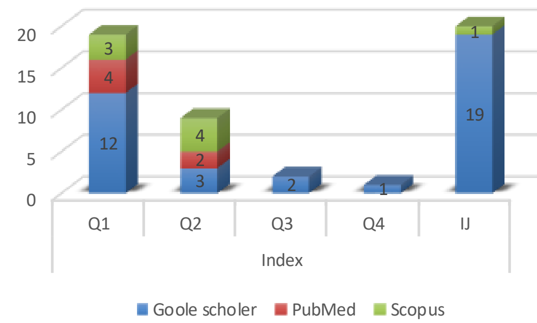

Fig. 2. Source and index of journal articles.

IV. RESULTS

A. Literature Research Characteristics

This study describes the characteristics of research on the application of AI for addressing stunting. These characteristics include Authors, Year, Publication, Publisher, Country, Journal Index, Subject Area, Data, Methodology, AI Model, and Evaluation Model. The main characteristics of the included articles are presented in Table III.

Most studies analyzed in this review utilize secondary datasets such as Demographic and Health Surveys (DHS) and national health surveys. These datasets typically include variables such as age, height, weight, gender, and socio-economic indicators. However, variations exist in dataset size, feature completeness, and data quality. Some studies involve large-scale national datasets, while others rely on smaller, localized datasets, which may introduce bias and affect model performance. Additionally, many datasets lack real-time updates and critical variables such as dietary intake, environmental factors, and genetic influences, which may limit the accuracy and generalizability of AI models.

TABLE III. LITERATURE RESEARCH CHARACTERISTICS INCLUDED IN THE REVIEW

Authors	Year	Publication	Publisher	Country	Subject Area	Data	Metode	[a]AI Model	Model Evaluasi
S Ankalaki, VG Biradar, et al. [18]	2024	International Journal of Online and Biomedical Engineering (iJOE)	International Association of Online Engineering	India	Classification of children's images based on nutritional status.	Image dataset of Healthy, Undernourished, Stunting, and Wasting children.	Deep learning	[b]CNN	Accuracy, Precision, Recall, F1-Score
Fenta HM, Zewotir T, et al. [19]	2021	BMC Medical Informatics and Decision Making	BioMed Central Ltd	Ethiopia	Prediction of severe malnutrition status in children.	Retrospective cross-sectional survey data.	Exploration and comparison of machine learning techniques.	[c]LR, LASSO, Elastic Net, [d]NN, [e]RF	Sensitivity, Specificity, Accuracy, [f]AUC
Nel S, Feucht UD, et al. [20]	2022	Maternal & Child Nutrition	Wiley-Blackwell Publishing Ltd	South Africa	Prediction of Severe Acute Malnutrition (SAM) risk.	Growth curve data.	[a]AI Model	[g]ANN	Sensitivity, Specificity, [h]ROC Curve Area

MA Haque, N Choudhury, et al., [21]	2023	BMJ Open	BMJ Publishing Group	Bangladesh	Prediction of stunting factors in children.	Cross-sectional study dataset.	Cluster randomised pre-post design, analisis statistic	[e]LR, [i]PR, [j]DT	[f]AUC, Sensitivity, Specificity, Classification Rate
MM Islam, MJ Rahman, et al. [22]	2022	International Journal of Cognitive Computing in Engineering	KeAi Communications Co.	Bangladesh	Prediction and Identification of Malnutrition Risk Factors.	Demographic and Health Survey (DHS) data.	Multinomial Logistic Regression (MLR).	[k]NB, [l]SVM, [j]DT, [g]ANN, [e]RF	[f]AUC
E A Turjo, M H Rahman, et al. [23]	2024	BMC Nutrition	BioMed Central Ltd	Bangladesh	Malnutrition Prediction.	Demographic and Health Survey (DHS) data.	Chi-Square Test	[k]NB, [j]DT, [m]CART, [e]LR, RF, [n]GBM	Accuracy, Sensitivity, Specificity, [o]PPV, [p]NPV, F1-Score, [f]AUC
X Wang, F Yang, et al. [24]	2023	Journal of Medical Internet Research	JMIR Publications Inc.	China	Malnutrition Diagnosis.	Multicenter observational cohort study data.	Machine Learning	[q]LGB, [r]MXGBoost, [e]RF.	[s]AUC ROC
Yalçın N, Kaşıkcı M, et al. [25]	2023	Scientific Reports	Nature Publishing Group	Turkey	Prediction of Birth Weight and Weight Gain in Infants.	NICU patient data.	Cross-validation	[e]RF, ENR	[s]AUROC, [t]R2
AU Salmah, AI Moedjiono, et al., [26]	2023	Pharmacognosy Journal	E-Manuscript Technologies	Indonesia	Early Detection of Stunting.	Community health worker, mother, and child data.	Quasi-experimental design	[u]NA	Paired t-test, Independent t-test,
K Fasna, SY Khan, et al. [27]	2024	Journal of Indian Society of Pedodontics and Preventive Dentistry	Wolters Kluwer Medknow Publications	India	Early Prediction of Malnutrition in Children.	Severe Acute Malnutrition (SAM) data	Intervention and preventive study.	[v]RT, [m]CART, [d]NN	[f]AUC
S Das, SA Basher, et al. [28]	2024	Journal of Population Economics	Springer New York	Bangladesh	Analysis of Stunting Trends in Children.	Demographic Survey Data	Bayesian multilevel time-series	Bayesian Model	[w]RMSE, [x]MAE, [t]R²
X Zhang, M Usman, et al. [29]	2024	ISPRS International Journal of Geo-Information	Multidisciplinary Digital Publishing Institute (MDPI)	Pakistan	Spatial Analysis of Stunting Disparities.	MICS Socioeconomic Data.	Multi-model OLS, Spatial Models, ML, EXAI	[y]OLS, [z]SDEM [aa]XGBoost, [e]RF, [ab]SHAP	[w]RMSE, [x]MAE, [t]R², [ac]LM
Shen H, Zhao H, et al. [30]	2023	Children (Basel)	Multidisciplinary Digital Publishing Institute (MDPI)	Papua New Guinea	Stunting Prediction	Demographic Health Survey Data	LASSO, Random-Forest Recursive Feature Elimination (RFE)	[e]LR, [j]DT, [l]SVM, [aa]XGBoost	[f]AUC, Accuracy, Precision, Recall, F1-Score
F H Bitew, C S Sparks, et al. [31]	2022	Public Health Nutrition	Cambridge University Press	Ethiopia	Stunting Prediction	Ethiopian Demographic and Health Survey	Feature selection, ML	[aa]XGBoost, [ad]K-NN, [e]RF, [d]NN, [ae]GLM	Accuracy Comparison Between Models
M Zribi, F Zaier, et al. [32]	2023	The European Journal of Public Health	Oxford University Press	Tunisia	Prediction of Double Burden of Malnutrition (DBM)	Tunisian Health Examination Survey (THES)	Feature Selection and Machine Learning Model Comparison	[k]NB, [l]SVM, [g]ANN, [aa]AdaBoost, [e]RF	Accuracy, Precision, recall, [f]AUC
R Qasrawi, S Sgahir, et al. [33]	2024	Children	Multidisciplinary Digital Publishing Institute (MDPI)	Palestine	Clustering Analysis of Stunting in Children	Child Data	Clustering	K-Means, [af]DBSCAN	Silhouette Score
Harrison E, Syed S, et al. [34]	2020	BMC pediatrics	BioMed Central Ltd	Pakistan	Prediction of Growth Patterns in Children at	Child Height-for-Age Z-Scores (HAZ) Data	Descriptive Analysis.	[e]RF	Accuracy

					Risk of Stunting.				
Begum N, Rahman MM, et al. [35]	2024	PLoS One	Public Library of Science	Bangladesh	Prediction of Nutritional Status in Pregnant Women.	Demographic and Health Survey Data (Cross-Sectional)	Feature transformation & machine learning classifiers	[e]RF	Accuracy, Kappa, Precision, Recall, F1-score.
J R Khan, J H Tomal, et al. [36]	2021	Informatics for Health and Social Care	Informa Healthcare	Bangladesh	Prediction of Stunting in Children	Demographic and Health Survey Data	Machine Learning	[ag]GBoost, [e]RF, [l]SVM, [ah]CT, [c]LR	Misclassification error, Accuracy, [f]AUC
P Timsina, HN Joshi, et al. [37]	2020	Journal of the American College of Nutrition	Taylor and Francis Ltd.	USA	Prediction of Malnutrition in Patients	Demographic, Anthropometric, and Clinical Data	Machine Learning	[e]RF	Sensitivity, Specificity, [f]AUC
O N Chilyabanyama, R Chilengi, et al. [4]	2022	Children	Multidisciplinary Digital Publishing Institute (MDPI)	Zambia	Prediction of Stunting in Children	Zambia Demographic and Health Survey (ZDHS) Data.	Machine Learning	[c]LR, [e]RF, [ai]SVC, [aa]XGBoost, [k]NB	Accuracy, Recall, Precision, F1-Score, Calibration Curve
E K Anku, H O Duah. [38]	2024	PLoS ONE	Public Library of Science	Ghana	Prediction of Malnutrition in Children	Multiple Indicator Cluster Survey (MICS) Data	Machine Learning	[aj]LDA, [ac]LM, [l]SVM, [e]RF, [ak]LASSO, [t]R2, [aa]XGBoost	Accuracy, Confusion Matrix, [f]AUC
M M Khudri, K K Rhee, et al. [39]	2023	PLoS ONE	Public Library of Science	USA	Prediction of BMI and Malnutrition in Women	Bangladesh Demographic and Health Survey (BDHS) Data	Machine Learning	[SVM], [ad]KNN	[w]RMSE, [x]MAE, Specificity, Cohen's Kappa, F1-Score, [f]AUC
S Ndagijimana, IH Kabano, et al. [40]	2023	Journal of Preventive Medicine and Public Health	Korean Society for Preventive Medicine	Rwanda	Prediction of Stunting in Children	Rwanda Demographic and Health Survey (RDHS) Data	Cross-Validation	[al]GBC	Accuracy Sensitivity, Specificity, F1-Score, [f]AUC
S Najaflou, M Rabiei, [41]	2021	International Journal of Web Research	IGI Publishing	Iran	Food Recommendation System for Children	Health Center Data	Descriptive Survey and Quantitative Analysis	Hybrid [am]AdaBoost, & [j]DT	Accuracy, validasi
MM Finucane, CJ Paciorek, et al. [42]	2015	Journal of the American Statistical Association	Taylor and Francis Ltd.	USA	Estimation of Z-Score Distribution for Undernutrition	Child Data	Distribution Model	[an]HB	[u]NA
A Muche, R Dewau, [43]	2021	Italian Journal of Pediatrics	BioMed Central Ltd	Ethiopia	Prediction of Stunting in Children	Community-Based Survey Data	Cross-sectional, Stratified Cluster Sampling	[c]LR	[ao]AOR, [ap]MOR, Confidence Interval ([aq]CI)
M Usman, K Kopczewska, [44]	2022	International Journal of Environmental Research and Public Health	Multidisciplinary Digital Publishing Institute (MDPI)	Pakistan	Determination of Stunting in Children	MICS Data	[ar]OLS Regression, Spatial Regression [as]SDEM, [aa]XGBoost	[ar]OLS, [as]SDEM, [aa]XGBoost	[at]AIC, [w]RMSE
B Sartorius, K Sartorius, et al. [45]	2020	BMJ open	BMJ Publishing Group	South Africa	Spatial and Temporal Trend Analysis of Malnutrition in Children	Child and Adult Survey Data	Multistage Random Sampling	[u]NA	[u]NA
Shams El Arifeen, Eva-Charlotte Ekstro¨m, et al. [46]	2018	International Journal of Epidemiology	Oxford University Press	Bangladesh	Nutritional Intervention Analysis	Longitudinal Data	Statistical Analysis & Survival Analysis	[au]CI	[au]CI

R Jain, RL Suman, et al. [11]	2017	International Journal of Contemporary Pediatrics	academia.edu	India	Anthropometric Status Analysis of Malnutrition	Data retrospektif	Descriptive Statistical Analysis and Z-Score	Distribusi Z-score & [av]MUAC	[u]NA
LE Smith, [47]	2018	The Journal of Nutrition	Haworth Press Inc.	Zimbabwe	Analysis of the Relationship Between Stunting and Wasting in Children	Child Longitudinal Data	Longitudinal Statistical Analysis	Z-score HAZ, [aw]WFH	[u]NA
S Choi, HM Yuen. et al.[48]	2018	Journal of Medical Internet Research	JMIR Publications Inc.	Ghana	Analysis of e-Learning Impact on Acute Malnutrition Management	Healthcare Worker and Medical Student Data	Longitudinal Study and Time-Series Analysis	[u]NA	[am]CI

[a]AI: artificial intelligence
[b]CNN: convolutional neural network.
[c]LR: logistic regression
[d]NN: neural network.
[e]RF: random forest
[f]AUC: Area Under the Curve
[GANN]: artificial neural network
[h]ROC: Receiver Operating Characteristic
[i]PR: Probabilistic
[j]DT: Decision Tree
[k]NB: Naïve Bayes
[SVM]: Support Vector Machine
[m]CART: Classification and Regression Tree
[n]GBM: Gradient Boosting Machines
[o]PPV: Positive Predictive Value
[p]NPV: Negative Predictive Value
[q]LGB: Light Gradient Boosting
[r]MXGBoost: Modified Extreme Gradient Boosting
[t]R2: elastic net regression
[u]NA: Not Available
[v]RT: random Tree
[w]RMSE: Root Mean Square Error
[x]MAE: Mean Absolute Error
[y]OLS: Ordinary Least Squares
[z]SDEM: Spatial Durbin Error Model
[aa]XGB: extreme gradient boosting
[ab]SHAP: Shapley Additive Explanations
[ac]LM: Logistic Model
[ad]KNN: k-nearest neighbor.
[ae]GLM: Generalized Linear Models
[af]DBSCAN Density-Based Spatial Clustering of Applications with Noise
[ag]GBoost: Gradient Boosting
[ah]CT: Clustering Technique
[ai]SVC: Support Vector Classifier
[aj]LDA: Latent Dirichlet Allocation
[ak]LASSO: least absolute shrinkage and selection operator.
[al]GBC: Gradient Boosting Classifier
[amt]AD: Adaptive Boosting
[ao]AOR: Adjusted Odds Ratio
[ap]MOR: Median Odds Ratio
[aq]CI: Confidence Interval
[at]AIC: Akaike Information Criterion
[av]MUAC: mid-upper arm circumference

B. Year and Method

This research on AI utilization for stunting has increased every year. This field has emerged as an ever more powerful trend, especially in the face of the rapid emergence of digital technology. The progress that resulted from the emergence of digital technologies is not only deserving of serious consideration but has also provided distinct challenges. Fig. 3 reflects the trend in AI research for stunting over the last decade.

The yearly publication count exhibited an upward trajectory in the previous 10 years of study between 2015 and 2024. A strong upward trend in articles dating back to 2021 (25%, 13/51) and robust growth through 2024 (55%, 28/51) were observed. In addition to the increasing number of articles, the quality was equally met, as 117 (61%; 31/51) articles were published in Q1, Q2, Q3, and Q4 journals. The observed increase in publications (Fig. 3) indicates a growing interest in AI applications for stunting, driven by advancements in digital health technologies and data availability.

Fig. 4 highlights the dominance of supervised machine learning methods, suggesting a strong reliance on predictive modeling approaches in public health datasets. On the other hand, four AI approach methods commonly used during the last decade (including AI methods and their implementations) for detecting, predicting, and tackling stunting were found. For example, DL, Statistical Methods, Supervised ML, and Unsupervised ML are some techniques. The Supervised ML method was used in the highest percentage of studies: over 79% of a total of 34 articles between 2015 and 2024. Fig. 4 summarizes the evolution of AI methods for stunting.

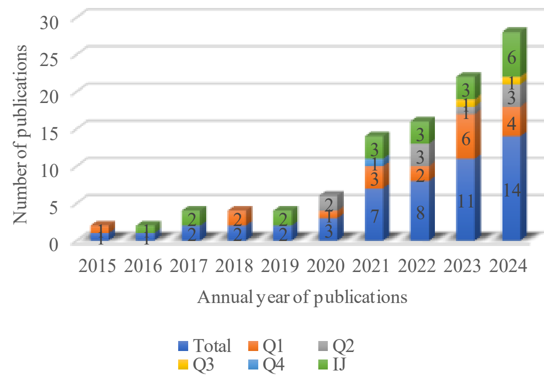

Fig. 3. Annual trend of the number of publications on AI and stunting.

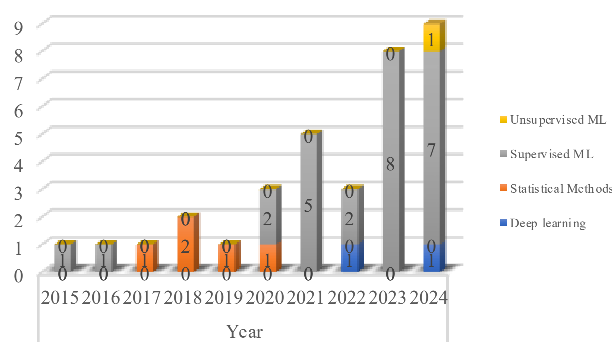

Fig. 4. Annual trend of the research method AI and stunting.

C. Research Sites and Subject Matter

Fig. 5. shows the characteristic location of countries (where the research is conducted). The five most researched places are: Indonesia (13 articles, 33%), [26], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [26], [57], [58], [59]; Bangladesh (8 articles, 14%) [21], [22], [23], [28], [35], [36], [60], [46]India (6 articles, 10.5%) [18], [27], [61], [62], [63], [64]; and Ethiopia, Pakistan, and the United States (USA), 3 articles (5.3%) [19], [31], [43], [29], [34], [44] and [37], [39], [42], respectively. More research is still needed to consider the use of artificial intelligence in the health sector, with a focus on stunting in unexplored areas. Additionally, developing countries should be considered more important than developed ones because of the different developmental contexts of those two types of countries. The geographical distribution shown in Fig. 5 reflects the higher research activity in developing countries, which correlates with the higher prevalence of stunting in these regions.

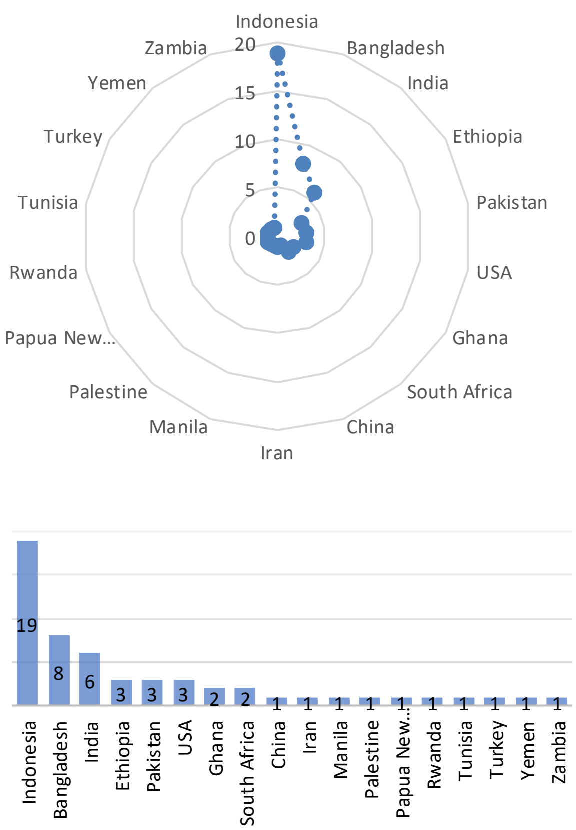

Fig. 5. Research location.

As illustrated in Fig. 6, the most studied subfield of the application of artificial intelligence for stunting is the prediction of stunting (e.g., prediction of the risk of Severe Acute Malnutrition (SAM), prediction and identification of malnutrition risk factors, prediction of Double Burden of Malnutrition (DBM), prediction of nutritional status, et al), with a contribution rate of 19.58%. The next subject area with maximum study includes stunting analysis (like stunting trend analysis, stunting clustering analysis, spatiotemporal malnutrition trend analysis, nutrition Intervention analysis & analysis of relationships between stunting, wasting & others), which represents about 8.24% of research. On the other hand, the subject areas that were the least explored are stunting and malnutrition diagnosis (2.6%), diagnosis of malnutrition (1.3%), and estimation of undernutrition z-score distributions (1.3%). Fig. 6 demonstrates that research is heavily concentrated on prediction tasks, while diagnostic and assessment-related studies remain limited, indicating potential areas for future exploration.

To His, this research would continue to expand and take root with the advent/formation of new phenomena/phenomena, as well for example/instance of rarely studied subjects, such as, for example, malnutrition diagnosis, image classification according to children's nutrition status, and others. AI applications across different subjects to develop solutions for stunting in a location or country could yield their own set of phenomena. It is because there is a disparity between developing and developed countries in terms of technologies, including computational technology, that should be taken into consideration while implementing AI-based solutions.

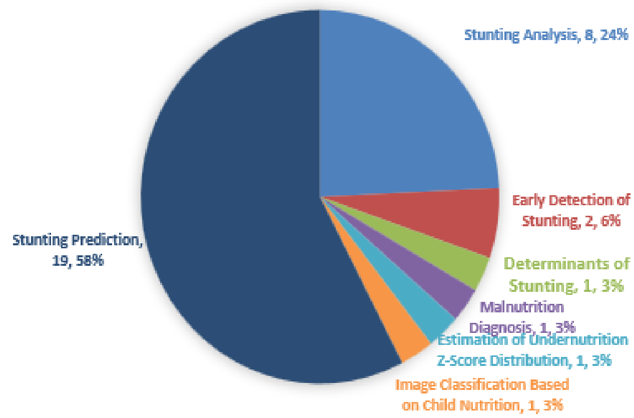

Fig. 6. Research subject matter.

D. The Algorithms and Evaluation Models of AI

Selection of an appropriate algorithm is an important part of AI to solve the stunting prevention issue in both accuracy and a reliable model. Algorithms widely used in time series forecasting are machine learning (ML) techniques, including Random Forest, Support Vector Machine (SVM), and Gradient Boosting, as well as deep learning (DL) methods such as Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) for sequential data. It has been demonstrated in this study that the Random Forest (RF) algorithm is the most commonly used in research for the prediction of stunting and malnutrition.

Some of the best-performing methods, such as Random Forest (RF), have gained prominence due to their adaptability to high-dimensional data and their capability to capture and represent important selected features. RF is a commonly used algorithm in the identification of malnourished children [19], [24] where LGBM and XGBoost (XGB) combined with RF were employed for malnutrition diagnosis. SVM is often applied to this data as well for its power of working with high-dimensional data and non-linear correlations as well. [22] utilized SVM to compare the performance against Naïve Bayes, Decision Tree, Artificial Neural Network (ANN), and RF for the prediction of malnutrition risk factors, while [30] employed SVM in conjunction with Logistic Regression and XGBoost to predict stunting. Additionally, Gradient Boosting Machines (GBM) algorithms, such as XGBoost and LGBM, are often used to improve prediction accuracy because these algorithms handle outliers more effectively. Also, in a study [24], LGBM and XGBoost outperformed other machine learning algorithms in malnutrition diagnosis, whilst in residual [31]XGBoost was combined with k-NN, Random Forest, and ANN to collect a relatively holistic stunting prediction.

Conversely, DL approaches are also finding more applications, especially in image analysis and complex pattern identification in health data. In studies that utilize images as input data, Convolutional Neural Network (CNN) is the most commonly used method. For example, the work of [18] used CNN to classify a child's pictures according to his /her nutritional status: Healthy, Undernourished, Stunting, and Wasting. Besides CNN, ANN is also commonly applied for predicting nutritional status, especially for classifying health data. ANN has the advantage of being able to identify patterns in the data that are difficult to work with through traditional Machine Learning (ML) algorithms. For instance, [20] employed an ANN to forecast the potential of Severe Acute Malnutrition (SAM), whereas in [22] ANN was compared with other techniques, including Naïve Bayes, SVM, Decision Tree, and Random Forest (RF). For example, Machine Learning and Deep Learning techniques are increasingly being applied to improve diagnostic accuracy and provide better insight into the drivers of stunting and malnutrition.

Different metrics, such as Accuracy, Sensitivity, Specificity, Precision-Recall, and AUC-ROC, are used to evaluate the models to classify whether a child is at risk of stunting or not. To prevent overfitting and ensure that the resulting model will generalize to new datasets, validation techniques, including cross-validation and confusion matrices, are also utilized. While the recent upturns may seem discouraging, grounded on optimal algorithms and well-considered evaluation, AI could emerge as a valuable partner in both measuring and anticipating stunting status in a more nuanced and evidence-based manner.

Evaluation models are vital in machine learning artificial intelligence (AI) for predicting and mitigating stunting and malnutrition, as the performance is reliant on these models. Accuracy: One of the most used evaluations; a correct percentage of the prediction with the data used. In contrast, when studies desire more specific detection (e.g., a generalizable prediction of acute malnutrition or prediction of Severe Acute Malnutrition (SAM), sensitivity and specificity metrics are frequently employed to allow balanced and accurate identification of positive and negative cases. Also, precision and recall are utilized in research that looks at reducing false positives and false negatives whilst making predictions, which is important in health-based systems in order to avoid diagnostic mistakes. The F1-score is the solution to the case of the distributed class, providing a single and more informative value than precision and recall taking into account both (precision, recall) values. AUC-ROC (Area Under the Curve - Receiver Operating Characteristics) has been a metric for model performance for predicting stunting versus non-stunting categories and malnutrition versus normal nutritional status in studies [30], [21].

Regression models and time-series analysis have specific metrics that are used to measure performance, besides classification model evaluation. Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are used as predictive measures commonly in research to predict nutritional status based on numerical factors like the Body Mass Index (BMI), including height and weight. For example, the study [39] was used RMSE and MAE to evaluate BMI and malnutrition level predictions using a regression approach. At the same time, in studies using clustering to allocate children according to the grouping of their nutritional status, it is common to use the Silhouette Score metric. As in the study [33]This metric was applied to measure the quality of clustering in stunting analysis based on machine learning. By employing several assessment strategies, public health-focused AI can keep growing, yielding predictive models that are more precise, dependable, and able to reveal here into the things that influence stunting and hunger.

E. AI Application Difficulties and Potentials in Stunting Solution

Learning that model's upcoming class of data poses one of the major challenges in establishing the underlying factors responsible for predicting stunting and malnutrition through artificial intelligence (AI). Most studies are based on survey data that often lack critical variables such as environmental moderators, dietary consumption patterns, or genetic effects. This can introduce bias into predictive models and inhibit their generalizability to larger populations. Additionally, the datasets used are generally not real-time, which limits the ability to perform early detection based on emerging trends. So one solution includes utilizing larger and real-time datasets, such as data from Electronic medical record systems or from Internet of Things-based health sensors. More data means less error in AI, allowing training on a wider array of factors that affect child growth.

Second is a very known problem which is a very common problem, which is the problem of overfitting in deep learning models. Models such as Convolutional Neural Network (CNN) or Artificial Neural Network (ANN) are known to perform best when trained on large amounts of data using feedforward processes. Overfitting is when the model is so well trained that it memorizes the patterns behind the training data, and hence becomes unable to generalize to data that it has not been exposed to before. That can cause the predictions to be less accurate when transferred to real-world situations. One solution to this problem involves using transfer learning, a method that adapts pre-trained AI models, built on large data sets, to smaller data sets without sacrificing accuracy. Moreover, hybrid models have also been proposed to improve performance in the absence of huge training sets, combining several machine learning and/or deep learning algorithms.

In addition, another key challenge is the black box nature of AI models and how harder it is to incorporate AI into public health systems. Models like Neural Networks and Gradient Boosting are black-box, and it is difficult for physician researchers and health professionals to interpret how these models arrive at decisions. Utilizing Explainable AI (XAI) approaches (e.g., SHAP - Shapley Additive Explanations, or LIME - Local Interpretable Model-Agnostic Explanations to provide visibility into the features that most impact AI decision-making can enhance transparency. Conversely, the challenges of implementing AI in public health systems also remain, such as inadequate digital infrastructure, a lack of access to AI technology by healthcare workers, and regulations that do not yet support the integration of AI. So, there is a need for more user-friendly AI systems with simple interfaces to support healthcare professionals and policymakers in making informed decisions. Thus, it is possible (AI) to be best used for early identification of stunting and malnutrition and better-tailored interventions.

F. Current Trends in AI Applications for Stunting Research

This data was obtained to better understand all published stunting studies, which were plotted using VOSviewer, a specialized software allowing visualization of relationships between studies, keyword analysis, and citation trends. Co-occurrence was used for the features in this bibliometric analysis, which included keywords, words in article titles, or terms in abstracts. Co-occurrence informs about topics or subtopics that co-occur in the scientific literature. Fig. 7 shows the network visualization of keyword relationships generated using the VOSviewer application.

The bibliometric analysis using VOSviewer reveals distinct research clusters related to stunting, malnutrition, and AI. The green cluster focuses on environmental and child health factors, highlighting the influence of infections, sanitation, and socio-economic conditions on nutritional status. In contrast, the red cluster emphasises nutritional status and the increasing application of AI and machine learning for predicting stunting risk, reflecting a growing trend toward AI-based predictive models in public health research.

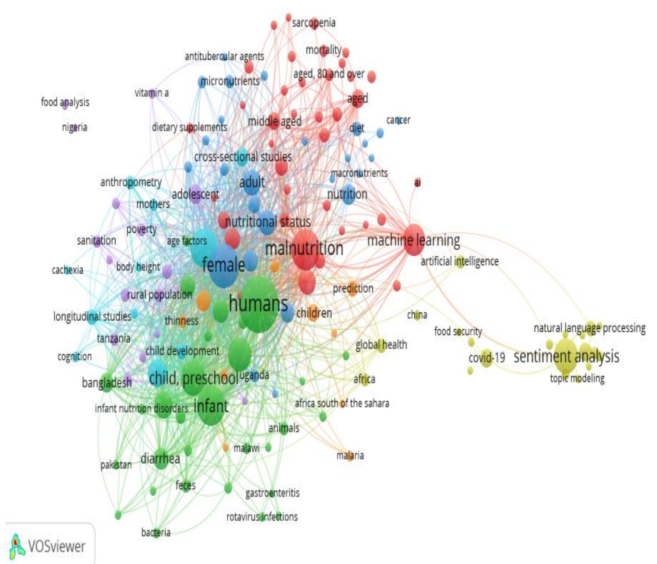

Fig. 7. Network visualization.

The yellow cluster highlights emerging stunting research areas, particularly the use of sentiment analysis and natural language processing (NLP). Keywords such as COVID-19 and food security indicate studies examining the pandemic's impact on child nutrition. These findings suggest that stunting research is increasingly integrating artificial intelligence, data analytics, and NLP techniques beyond traditional nutritional and health determinants, providing a foundation for future interdisciplinary research on stunting prevention and intervention.

The Overlay Visualization generated using VOSviewer (Fig. 8) shows a rapid increase in research on stunting, malnutrition, and artificial intelligence in recent years. The color gradient represents temporal differences in keywords, with blue indicating earlier research themes (2018–2019) and yellow reflecting more recent trends (2021–2022). Based on this visualization, three major research trends in stunting can be identified according to their temporal evolution.

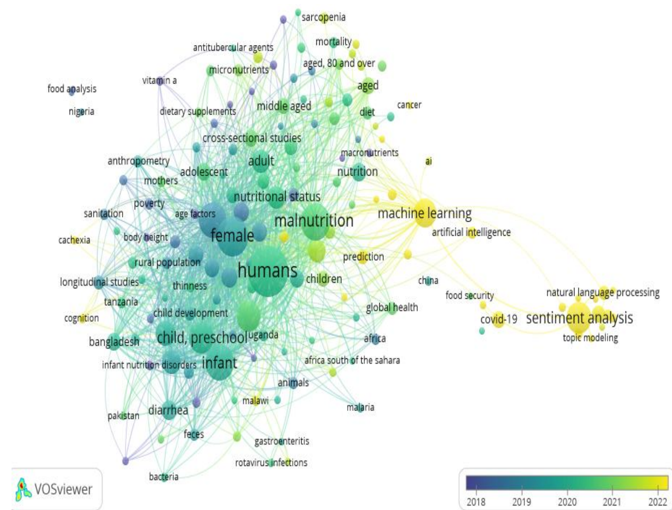

Fig. 8. Overlay visualization

The blue–green cluster (2018–2020) indicates that earlier studies focused on basic health determinants such as nutrition, infections, and socio-economic conditions. More recent trends (2021–2022), represented by the yellow cluster, highlight the application of artificial intelligence, particularly machine learning and health prediction. In addition, text-based and data analytics approaches, including natural language processing and sentiment analysis, have increasingly emerged, with COVID-19 and food security acting as key drivers of recent stunting and malnutrition research. These patterns reflect a growing multidisciplinary, AI-driven approach to understanding and addressing stunting.

V. Discussion

The findings of this study demonstrate a significant increase in the application of Artificial Intelligence (AI) for stunting research over the last decade. The upward trend in publications, particularly after 2021, indicates a growing recognition of AI as a powerful tool in addressing complex public health problems. This surge is closely associated with the rapid advancement of digital technologies and the increased availability of health-related data. Moreover, the fact that the majority of studies were published in indexed journals (Q1–Q4) reflects not only the growing quantity but also the improving quality and scientific rigor of research in this field.

From a methodological perspective, supervised machine learning dominates the landscape, accounting for more than 79% of the reviewed studies. This dominance suggests a strong preference for predictive modeling approaches, particularly in structured datasets commonly found in public health. While deep learning methods are gaining attention, their adoption remains limited compared to traditional machine learning techniques. This may be attributed to the higher computational requirements and the need for large-scale datasets in deep learning applications, which are often unavailable in many public health contexts, especially in developing countries.

Geographically, the concentration of studies in developing countries such as Indonesia, Bangladesh, and India highlights the urgency of addressing stunting in these regions. These countries share similar socio-economic conditions, healthcare infrastructures, and nutritional challenges, which explains the high research activity. However, this concentration also raises concerns regarding the generalizability of AI models. Models developed using data from developing countries may not perform optimally when applied to populations in developed countries due to differences in demographic characteristics and health systems. Therefore, cross-country validation and the use of more diverse datasets are essential to enhance model robustness and applicability.

In terms of research focus, the predominance of stunting prediction (19.58%) indicates that early detection remains the primary objective of AI applications in this domain. This aligns with public health priorities, where early identification of at-risk children is crucial for timely intervention. However, other important areas, such as diagnosis and nutritional status estimation, remain underexplored. This imbalance suggests a research gap and highlights opportunities for future studies to expand into less-studied areas, including image-based diagnosis and advanced nutritional assessment methods.

Regarding algorithm selection, Random Forest emerges as the most frequently used method due to its robustness, ability to handle high-dimensional data, and interpretability. Other algorithms, such as Support Vector Machine (SVM) and Gradient Boosting (e.g., XGBoost and LGBM), are also widely used, particularly for their strong predictive performance and ability to manage complex, non-linear relationships. Meanwhile, deep learning approaches such as Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN) show promising results, especially in image-based and complex data analysis. However, their effectiveness is often constrained by limited data availability and the risk of overfitting.

Evaluation metrics play a crucial role in ensuring model reliability. The frequent use of metrics such as accuracy, precision, recall, F1-score, and AUC-ROC indicates a comprehensive approach to performance assessment. In addition, validation techniques such as cross-validation and confusion matrices are widely applied to prevent overfitting and ensure generalizability. For regression and clustering tasks, metrics such as RMSE, MAE, and Silhouette Score further support the robustness of AI models in different analytical contexts.

Despite these advancements, several challenges remain. One major issue is the limited availability of high-quality and real-time datasets. Most studies rely on survey-based data, which may lack important variables such as environmental factors, dietary patterns, and genetic influences. This limitation can reduce model accuracy and hinder early detection capabilities. Furthermore, the black-box nature of many AI models presents challenges in interpretability, making it difficult for healthcare professionals to trust and adopt these systems. The integration of Explainable AI (XAI) techniques, such as SHAP and LIME, is therefore essential to improve transparency and usability.

Another critical challenge is the implementation of AI in real-world public health systems. Issues such as limited digital infrastructure, lack of technical expertise among healthcare workers, and insufficient regulatory frameworks can hinder the adoption of AI-based solutions. Consequently, there is a need for more user-friendly AI systems with simple interfaces to support healthcare professionals and policymakers in making informed decisions.

Finally, bibliometric analysis reveals a shift toward more interdisciplinary and data-driven research trends. The integration of AI with natural language processing (NLP), sentiment analysis, and big data analytics reflects the evolving nature of stunting research. Emerging topics such as COVID-19 and food security further demonstrate how global events influence research directions. This indicates that future research will likely adopt a more holistic and multidisciplinary approach, combining traditional public health knowledge with advanced AI techniques to address stunting more effectively.

In summary, while AI has shown great potential in improving stunting prediction and intervention, further efforts are needed to address data limitations, enhance model interpretability, and ensure practical implementation. Strengthening collaboration across countries and disciplines will be key to maximizing the impact of AI in tackling stunting as a global public health challenge.

VI. Conclusion

Artificial intelligence (AI) in public health research has come a long way in the past 10 years. Machine learning (ML) and deep learning (DL) are among the many prediction methods used to forecast children’s nutritional condition based on variables. Some of the applied algorithms include Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting, which have demonstrated effectiveness for high-accuracy processing of health survey data. Within this context, deep learning (DL) methods, followed by CNN and artificial neural networks (ANN), are being progressively used for image data manipulation and children's nutritional status classification. Different metrics, such as accuracy, sensitivity, specificity, AUC-ROC, and F1-score, are used to evaluate the model to maintain the model's reliability among diverse research settings.

While the potential of AI is evident from its proven efficacy, several challenges need to be overcome. One significant challenge is streamlining data, as much existing research still depends on survey data that do not always mirror present-day conditions and typically do not sufficiently take environmental and genetic contributors into consideration. Furthermore, complicated AIs, most notably deep learning, are often not interpretable to health practitioners and policymakers. Thus, the need for the development of Explainable AI (XAI) to improve model intelligibility. The bibliometric mapping analysis provided by VOSviewer indicates that future research trends will involve the integration of AI with the Internet of Things (IoT) for real-time nutritional status monitoring and the application of multimodal AI models encompassing clinical, genetic, and socio-economic factors research areas. With these advancements, AI could potentially play a greater role in advancing better global health policy and scaling interventions.

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