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AI-ASSISTED EARLY RISK PREDICTION OF CHILDHOOD MALNUTRITION USING MATERNAL, NUTRITIONAL, AND CLINICAL INDICATORS IN PAKISTAN

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Abstract

Childhood malnutrition remains a major public-health challenge in Pakistan, requiring timely identification of children at elevated risk. This study examined the potential of artificial intelligence (AI)-assisted predictive modelling to identify childhood malnutrition using integrated maternal, nutritional, and clinical indicators. A quantitative, cross-sectional predictive design was adopted using secondary survey data. Multiple machine-learning algorithms, including logistic regression, decision tree, naïve Bayes, support vector machine, Random Forest, and Gradient Boosting, were evaluated using accuracy, precision, recall, F1-score, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). Explainable AI using SHAP was applied to identify the relative contribution and direction of key predictors. The findings indicated that Gradient Boosting produced the strongest predictive performance, achieving 83.1% accuracy, an F1-score of 82.0%, and an AUC of .90. Child age, dietary diversity, maternal BMI, clinical risk indicators, and maternal education emerged as important predictors of malnutrition risk. The findings suggest that integrating multidimensional indicators can improve early identification of nutritional vulnerability compared with conventional single-factor assessment. The application of SHAP further enhanced model transparency by identifying the principal factors underlying individual risk predictions. The study contributes to AI-enabled preventive healthcare by proposing an interpretable predictive framework that can complement conventional nutritional screening and support earlier, targeted intervention in Pakistan.

INTRODUCTION

Childhood malnutrition remains a major public-health challenge in low- and middle-income countries, with consequences extending from impaired physical growth and cognitive development to increased susceptibility to infection, reduced educational attainment, and diminished productivity later in life. In Pakistan, undernutrition among children under five remains particularly concerning, with stunting, wasting, and underweight continuing to affect substantial proportions of the child population. Recent evidence identifies maternal education, maternal nutritional status, household socioeconomic conditions, breastfeeding and complementary-feeding practices, birth

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characteristics, water and sanitation, and geographic inequalities as important determinants of childhood nutritional outcomes in Pakistan. Childhood malnutrition is not generated by a single risk factor; rather, it emerges from interactions among maternal, nutritional, clinical, household, and environmental conditions. Maternal nutritional status and education influence fetal growth, infant feeding practices, healthcare utilization, and the quality of childcare. Similarly, inadequate dietary diversity, low birth size, poor sanitation, recurrent illness, and household economic deprivation can interact to increase vulnerability to stunting, wasting, and underweight. Evidence from Pakistan indicates that maternal body mass index, maternal education, household wealth, breastfeeding, birth size, water quality, and child age are among the factors associated with anthropometric failure.

Traditional approaches to identifying children at risk of malnutrition have generally relied on statistical associations, screening criteria, and clinical or anthropometric thresholds. Although these approaches remain important, they may have limited capacity to capture nonlinear relationships and complex interactions among numerous risk factors. Artificial intelligence (AI) and machine-learning techniques provide an opportunity to move beyond conventional risk-factor analysis toward individualized and early prediction. A recent systematic review of AI applications in malnutrition reported growing use of machine-learning approaches for automated screening and early detection, while also identifying challenges concerning data quality, interpretability, validation, and clinical implementation.

Recent empirical research further demonstrates the potential of machine learning for childhood malnutrition prediction. A 2025 meta-analysis of studies using Demographic and Health Survey data found that machine-learning models demonstrated moderate-to-good predictive performance for stunting, wasting, and underweight, although substantial heterogeneity existed across studies. Importantly, recent Pakistan-specific research has applied Random Forest, Support Vector Machine, Naïve Bayes, and AdaBoost to predict stunting, wasting, and underweight using nationally representative data. The findings demonstrate that machine-learning models can identify complex combinations of socioeconomic and health-related predictors that are relevant to childhood malnutrition.

More recent evidence from Pakistan has strengthened the case for combining predictive modelling with explainable artificial intelligence. Research using 4,098 Pakistani children from the 2017–2018 Pakistan Demographic and Health Survey compared machine-learning-enhanced logistic regression with conventional logistic regression and incorporated SHAP-based explanations. The study reported that machine learning captured additional predictors, including maternal BMI, employment, and dietary diversity, while SHAP analysis provided greater insight into the direction and relative contribution of individual risk factors. These findings are important because a clinically useful prediction system should not merely classify a child as high or low risk; it should also provide interpretable information about the factors contributing to that risk.

Despite these developments, an important research opportunity remains. Existing Pakistan-specific studies have predominantly focused on retrospective identification of determinants or prediction of established nutritional outcomes using demographic and socioeconomic variables. Less attention has been given to an integrated AI-assisted early-risk framework that simultaneously incorporates maternal, nutritional, and clinical indicators and translates these indicators into an interpretable risk prediction mechanism. International research has demonstrated the feasibility of using routinely collected clinical and nutritional indicators for forecasting acute malnutrition, suggesting that AI-based systems can potentially support earlier identification and targeted intervention.

Therefore, the present study proposes an AI-assisted early risk prediction framework for childhood malnutrition in Pakistan, integrating maternal characteristics, nutritional indicators, and clinical information. By examining the predictive contribution of these multidimensional

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indicators and evaluating machine-learning performance, the study seeks to develop a technically rigorous and practically interpretable approach to identifying children who may be vulnerable to malnutrition before severe nutritional deterioration occurs. Such an approach could complement existing screening and public-health systems by supporting more timely identification, prioritization, and intervention.

Problem Statement

Childhood malnutrition in Pakistan represents a multidimensional public-health problem shaped by interacting maternal, nutritional, clinical, socioeconomic, and environmental factors. Although national and population-based evidence has established the importance of maternal education, maternal nutritional status, household economic conditions, breastfeeding, dietary practices, birth characteristics, sanitation, and geographical disparities, the identification of children at elevated risk still largely depends on conventional indicators and retrospective assessment. Such approaches may identify nutritional deterioration after it has become clinically or anthropometrically apparent rather than sufficiently early to support preventive intervention.

The complexity of malnutrition makes early prediction particularly challenging. Maternal characteristics can influence birth outcomes and infant feeding; dietary adequacy interacts with age and health status; and clinical conditions may alter nutritional requirements and vulnerability. These relationships may be nonlinear and interactive, making them difficult to represent adequately through conventional statistical models. Recent evidence from Pakistan demonstrates that machine-learning approaches can identify a broader range of nutritional risk factors than conventional logistic regression and can reveal heterogeneous relationships that may otherwise remain undetected.

However, important methodological and contextual gaps remain. First, much of the existing literature focuses on predicting individual outcomes such as stunting, wasting, or underweight rather than developing a multidimensional early-risk framework based on maternal, nutritional, and clinical indicators. Second, predictive accuracy alone is insufficient for public-health implementation because health professionals require understandable explanations of why a particular child is classified as high risk. Third, many existing models are developed using retrospective survey data, creating uncertainty about their usefulness for early screening and routine decision support. Finally, although machine learning has demonstrated potential in malnutrition research internationally, evidence remains comparatively limited regarding integrated and explainable AI-assisted prediction specifically tailored to Pakistan's maternal and child health context.

The problem, therefore, is not simply the persistence of childhood malnutrition but the limited availability of an integrated, accurate, and interpretable mechanism for identifying children at elevated risk before malnutrition becomes severe. Addressing this gap requires a predictive framework capable of combining multiple categories of information while maintaining sufficient interpretability for health practitioners and policymakers. The proposed study responds to this need by examining whether AI-based predictive techniques can effectively integrate maternal, nutritional, and clinical indicators to identify childhood malnutrition risk in Pakistan.

Research Questions

1. Which maternal, nutritional, and clinical indicators are significantly associated with the risk of childhood malnutrition in Pakistan?
2. To what extent can AI and machine-learning models accurately predict childhood malnutrition using maternal, nutritional, and clinical indicators?
3. Which machine-learning algorithm provides the most reliable predictive performance for identifying children at elevated risk of malnutrition?
4. What are the relative contributions of maternal, nutritional, and clinical indicators to the predicted risk of childhood malnutrition?

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5. How can explainable AI techniques improve the interpretability of childhood malnutrition risk predictions for healthcare and public-health decision-making?

Research Objectives

1. To identify and evaluate maternal, nutritional, and clinical indicators associated with childhood malnutrition in Pakistan.
2. To develop AI-based machine-learning models for early prediction of childhood malnutrition using multidimensional maternal, nutritional, and clinical data.
3. To compare the predictive performance of alternative machine-learning algorithms using appropriate performance measures, including accuracy, precision, recall, F1-score, sensitivity, specificity, and area under the receiver operating characteristic curve.
4. To determine the relative importance of maternal, nutritional, and clinical indicators in predicting childhood malnutrition risk.
5. To apply explainable AI techniques to interpret model predictions and identify the key factors contributing to individual and population-level malnutrition risk.
6. To develop evidence-based recommendations for incorporating AI-assisted early risk prediction into child nutrition screening and preventive health interventions in Pakistan.

Significance of the Study

Theoretical Significance

The study contributes to the emerging intersection of artificial intelligence, predictive healthcare, maternal-child nutrition, and public-health analytics. It extends conventional malnutrition research from explanatory identification of risk factors toward multidimensional predictive modelling. By integrating maternal, nutritional, and clinical indicators within an AI framework, the study can contribute evidence concerning how machine-learning approaches capture complex and potentially nonlinear relationships underlying childhood nutritional vulnerability.

Practical Significance

The study has potential practical value for healthcare professionals, nutritionists, community health workers, and child-health programmes. An accurate and interpretable prediction model could help identify children who require closer nutritional monitoring or further clinical assessment. Rather than relying exclusively on the detection of established malnutrition, an AI-assisted system could support risk stratification and earlier preventive action. This is particularly relevant where healthcare resources are constrained and targeted intervention is necessary.

Policy Significance

At the policy level, the findings can provide evidence for strengthening data-driven maternal and child nutrition programmes in Pakistan. Predictive models could potentially support the prioritization of high-risk communities and children, improve allocation of nutritional resources, and complement existing screening systems. Explainable AI is especially relevant because policy and clinical stakeholders need transparent evidence about the factors underlying predicted risk rather than relying solely on opaque algorithmic classifications. Recent Pakistan-specific research similarly emphasizes the value of interpretable machine learning for translating predictive analytics into policy-relevant nutritional interventions.

Public-Health Significance

The broader significance lies in shifting the focus from reactive identification of malnutrition to proactive risk prediction. Given the continuing burden of childhood undernutrition in Pakistan, an evidence-based AI-assisted approach could potentially facilitate earlier identification of vulnerable children and support timely nutritional, maternal, and clinical interventions. The study therefore addresses both a methodological need for improved prediction and a public-health need for earlier and more targeted prevention.

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Literature Review

Childhood malnutrition is a complex outcome produced by the interaction of biological, maternal, nutritional, socioeconomic, environmental, and healthcare-related factors. Consequently, conventional approaches that examine individual determinants independently may not adequately represent the multidimensional and potentially nonlinear processes through which nutritional vulnerability develops. Recent research increasingly supports the use of artificial intelligence (AI) and machine-learning (ML) techniques for identifying complex patterns in child-health data and improving early nutritional risk prediction. A systematic review by Janssen et al. (2024) found that AI applications in malnutrition increasingly employ supervised learning for automated screening and detection. However, the review also identified a major implementation problem: most developed AI models have not progressed into routine clinical practice, highlighting the importance of validation, interpretability, usability, and integration into healthcare workflows.

Childhood Malnutrition and Multidimensional Risk Factors

The literature consistently demonstrates that childhood malnutrition cannot be adequately explained by child-level nutritional intake alone. Maternal characteristics, household resources, birth conditions, feeding practices, sanitation, and access to healthcare jointly influence nutritional outcomes. Recent Pakistan-specific evidence confirms the importance of these multidimensional determinants. A study based on the Composite Index of Anthropometric Failure found that child age, small birth size, lack of breastfeeding, maternal education, household economic status, water quality, and maternal BMI were associated with anthropometric failure, while regional differences were particularly evident for wasting.

These findings have an important implication for predictive modelling. A model restricted to anthropometric measurements or dietary variables may omit upstream determinants that contribute to nutritional deterioration. Conversely, a model incorporating maternal, nutritional, clinical, and contextual characteristics can potentially capture a broader risk profile. Thus, the present study's integration of maternal, nutritional, and clinical indicators is theoretically and empirically consistent with the multidimensional nature of childhood malnutrition.

Application of Machine Learning to Childhood Malnutrition

Machine learning offers an alternative to conventional statistical modelling because it can accommodate numerous predictors and identify complex relationships without requiring all relationships to follow a predetermined functional form. Rao et al. (2025), in a meta-analysis of ML applications using Demographic and Health Survey data, identified 11 eligible studies involving children under five. The pooled evidence indicated moderate-to-good predictive performance for stunting, wasting, and underweight, although the very high heterogeneity across studies indicates that predictive performance varies substantially according to population, data characteristics, outcome definition, and modelling strategy.

The meta-analysis also exposes an important geographical limitation. More than half of the included studies originated from Bangladesh, while evidence from other South Asian settings was comparatively limited. Therefore, predictive models developed in one country cannot automatically be assumed to perform similarly in Pakistan. Differences in maternal health, dietary practices, household socioeconomic conditions, healthcare access, disease burden, and regional environments can alter the relationships between predictors and malnutrition. This strengthens the justification for developing and evaluating Pakistan-specific prediction models.

Pakistan-Specific Machine-Learning Evidence

Recent research has begun addressing this gap directly. Saleem and Jiang (2025) developed ML models for predicting stunting, wasting, and underweight among Pakistani children using the Pakistan Demographic and Health Survey 2017–2018. Their study demonstrates the feasibility of

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applying ML approaches to nationally representative Pakistani data and provides evidence that predictive modelling can identify meaningful combinations of socioeconomic and health-related variables

An especially important contribution is the Pakistan-specific comparison between machine-learning-enhanced logistic regression and conventional logistic regression reported by Shahid et al. (2026). Using 4,098 children from the 2017–2018 Pakistan Demographic and Health Survey, the authors reported substantial levels of stunting, underweight, and wasting and demonstrated that the ML-enhanced approach identified a broader set of relevant predictors than conventional logistic regression. Maternal BMI, maternal employment, dietary diversity, child age, maternal education, birth order, water quality, and other characteristics contributed to prediction.

This research is particularly relevant to the proposed study because it demonstrates that the relationships between nutritional predictors and outcomes may be heterogeneous and context-dependent. For example, dietary diversity was not simply a linear determinant; its contribution differed according to whether adequate dietary diversity was present. Such findings illustrate why ML approaches may be valuable when the objective is prediction rather than only estimation of average associations.

Maternal Indicators as Predictors of Childhood Malnutrition

Maternal characteristics are particularly important because maternal health and socioeconomic conditions influence fetal growth, birth outcomes, breastfeeding, complementary feeding, healthcare utilization, and the child's nutritional environment. Evidence from Pakistan indicates that maternal BMI, maternal education, and employment can contribute to the prediction of child nutritional outcomes. The recent ML-LR study further identified maternal BMI and maternal employment among predictors that conventional logistic regression did not identify as significant.

Maternal education is similarly important because it may influence health literacy, feeding decisions, healthcare-seeking behaviour, hygiene practices, and the ability to implement recommended child-care practices. Pakistan-specific evidence indicates that maternal education is associated with childhood nutritional outcomes, reinforcing its inclusion in predictive frameworks.

Therefore, maternal variables should not be regarded merely as background demographic controls. In an early-risk prediction framework, they can represent upstream determinants that help characterize the child's nutritional vulnerability before severe anthropometric deterioration occurs.

Nutritional Indicators and Dietary Diversity

Nutritional indicators provide a more proximal representation of a child's nutritional condition. Dietary diversity, breastfeeding, birth size, feeding practices, and anthropometric measures are repeatedly identified in the literature as relevant to childhood nutrition. Pakistan-specific research has shown associations between breastfeeding, birth size, dietary practices, and nutritional outcomes.

The recent application of SHAP-based ML modelling provides additional evidence that nutritional indicators may operate in complex ways. Shahid et al. (2026) found that dietary diversity contributed substantially to prediction and demonstrated that inadequate dietary diversity increased predicted risk, whereas adequate diversity had a protective contribution. This finding is methodologically significant because it illustrates how explainable ML can move beyond identifying whether a variable is statistically associated with malnutrition and instead show how particular predictor values contribute to an individual prediction.

Clinical Indicators and Early Detection

Clinical indicators are also important because illness and nutritional status interact bidirectionally. Recurrent disease, impaired health status, and other clinical conditions can increase nutritional vulnerability, while malnutrition can simultaneously increase susceptibility to infection and adverse health outcomes. An early prediction

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system that incorporates clinical indicators may therefore identify risk that is not apparent from socioeconomic or dietary information alone.

The broader AI-malnutrition literature supports this direction. Janssen et al. (2024) found that AI-based malnutrition research has employed multiple types of patient, screening, and clinical information, with supervised learning representing a dominant modelling approach. However, the authors emphasized the substantial gap between model development and real-world implementation. For the proposed study, this suggests that clinical indicators should be selected not merely because they improve statistical performance, but because they are realistically measurable and potentially usable within routine maternal and child healthcare.

Explainable Artificial Intelligence and Prediction Transparency

Predictive accuracy alone is insufficient for a health-related AI system. Healthcare professionals and policymakers need to understand why a model classifies a child as high risk. Explainable AI (XAI), particularly SHAP-based methods, provides a mechanism for examining the contribution of individual predictors to model outputs.

The recent Pakistan-specific study by Shahid et al. (2026) demonstrates the value of this approach. SHAP analysis identified the relative contribution of variables such as child age, maternal BMI, maternal employment, water quality, dietary diversity, and maternal education, while also demonstrating that some predictors could have different effects depending on their values.

This represents an important methodological advancement over conventional black-box prediction. For the proposed study, explainability can help transform an algorithmic risk score into actionable information—for example, distinguishing whether elevated predicted risk is primarily associated with maternal nutritional status, inadequate dietary diversity, clinical vulnerability, or other factors. Such information can improve the potential usefulness of the model for screening and targeted intervention.

Critical Research Gap

Despite the rapid development of AI-based nutritional prediction, several gaps remain. First, the global evidence base is still relatively small. The 2025 meta-analysis identified only 11 eligible DHS-based studies and reported substantial heterogeneity across predictive models. Second, existing research is geographically concentrated, limiting the generalizability of findings to Pakistan and other contexts.

Third, Pakistan-specific research has demonstrated the feasibility of ML prediction, but existing studies have largely focused on predicting established nutritional outcomes such as stunting, wasting, and underweight using demographic, socioeconomic, and health variables. There remains scope for an integrated framework explicitly designed around early risk prediction using three complementary domains: maternal indicators, nutritional indicators, and clinical indicators.

Fourth, there is an important distinction between prediction and explanation. A model may achieve high predictive performance while providing little practical information about why a particular child is classified as high risk. The emerging use of SHAP demonstrates how this limitation can be addressed, but explainable AI remains insufficiently integrated into child-malnutrition prediction research.

Finally, the literature reveals an implementation gap. Janssen et al. (2024) reported that more than 90% of identified AI models for malnutrition were not being used in routine clinical practice. Therefore, future research should not focus exclusively on algorithmic accuracy; it should also consider interpretability, clinically meaningful indicators, validation, usability, and potential integration into existing child-health systems.

The proposed study addresses these gaps by developing an AI-assisted, multidimensional, and explainable early-risk prediction framework specifically for childhood malnutrition in Pakistan. Its central contribution is the integration of maternal, nutritional, and clinical information within a predictive rather than purely explanatory framework.

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Underpinning Theory

Dynamic Capabilities Theory

Dynamic Capabilities Theory (DCT), originally developed by Teece et al. (1997) and subsequently elaborated by Teece (2007), provides a suitable theoretical foundation for the present study. The theory explains how organizations develop, integrate, reconfigure, and deploy resources and capabilities to respond to changing environments. Although DCT originated primarily in strategic management, its central logic can be extended to healthcare and public-health systems in which organizations must transform available information and technological resources into improved decision-making capabilities.

The theory is particularly applicable to an AI-assisted childhood malnutrition prediction system because the proposed framework does not treat AI as an isolated technological instrument. Rather, AI represents a capability through which existing maternal, nutritional, and clinical information can be sensed, interpreted, and translated into timely risk-management decisions.

Sensing

The first dimension of DCT is sensing, referring to the ability to identify and interpret emerging conditions and risks. In the context of childhood malnutrition, AI-based predictive models can enhance the sensing capability of healthcare systems by identifying patterns across maternal, nutritional, and clinical indicators that may not be readily detectable through conventional assessment. Instead of waiting until malnutrition becomes clinically evident, predictive analytics can potentially identify children exhibiting combinations of risk factors associated with future nutritional deterioration.

Seizing

The second dimension is seizing, which involves mobilizing resources and taking appropriate action in response to identified opportunities or threats. In this study, a predicted high-risk child represents a signal requiring potential preventive action. Healthcare professionals can use model outputs to prioritize nutritional counselling, clinical assessment, feeding interventions, maternal support, or closer monitoring. Thus, AI converts heterogeneous health information into decision-support information.

Reconfiguring

The third dimension is reconfiguring or transforming, referring to the ability to modify existing resources, processes, and capabilities in response to changing conditions. An AI-assisted nutrition system can support the reconfiguration of conventional screening processes by integrating routinely collected information into a predictive decision-support mechanism. Rather than relying exclusively on periodic identification of established malnutrition, health systems can potentially incorporate continuous or repeated risk assessment into preventive child-health services.

Justification for the Theory

DCT is particularly appropriate because the proposed study concerns more than the statistical relationship between predictors and malnutrition. Its underlying objective is to understand how data and AI capabilities can improve early identification and management of nutritional risk.

The theory provides a logical connection among:

Maternal, nutritional and clinical resources → AI-enabled sensing → early risk identification → targeted intervention → improved child-health decision-making.

The recent AI-malnutrition literature supports this capability-oriented. AI systems have demonstrated potential for earlier nutritional screening, but their translation into routine practice remains limited. Similarly, Pakistan-specific research demonstrates that ML and SHAP can identify complex and context-dependent nutritional risk factors that conventional models may overlook. (DCT therefore provides a useful theoretical lens for explaining why the effective value of AI lies not simply in algorithmic sophistication but in the capability to transform dispersed health information into actionable early-risk intelligence.

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Hypotheses

Based on the literature and Dynamic Capabilities Theory, the following directional hypotheses are proposed:

H1: Maternal risk indicators have a positive and significant effect on the likelihood of childhood malnutrition in Pakistan.

H2: Inadequate nutritional indicators have a positive and significant effect on the likelihood of childhood malnutrition in Pakistan.

H3: Adverse clinical indicators have a positive and significant effect on the likelihood of childhood malnutrition in Pakistan.

H4: Maternal, nutritional, and clinical indicators significantly improve the predictive performance of AI-based models for childhood malnutrition.

H5: The integration of maternal, nutritional, and clinical indicators positively enhances the accuracy of early AI-assisted malnutrition risk prediction.

H6: Explainable AI-based identification of key risk indicators significantly improves the interpretability of childhood malnutrition risk predictions.

Methodology

Research Design

The study employed a quantitative, cross-sectional predictive research design to examine the effectiveness of artificial intelligence (AI) and machine-learning techniques in predicting childhood malnutrition in Pakistan. The design was appropriate because the study examined the predictive relationships between maternal, nutritional, and clinical indicators and childhood malnutrition outcomes using structured quantitative data. The study followed a predictive analytics framework in which relevant indicators were used as input variables and childhood nutritional status was treated as the dependent outcome. Multiple machine-learning algorithms were subsequently compared to determine their predictive performance.

Population

The study population comprised children under five years of age and their mothers/caregivers in Pakistan. The target population represented households covered by nationally representative maternal and child-health data. Maternal characteristics, child demographic information, nutritional indicators, and relevant clinical/health indicators were considered for model development.

For empirical analysis, secondary data from the Pakistan Demographic and Health Survey (PDHS) 2017–18 were utilized. The PDHS provided nationally representative information on women, children, household characteristics, maternal health, child health, and nutritional outcomes and therefore provided an appropriate data source for developing a Pakistan-specific malnutrition prediction model.

Sampling Technique

A multistage probability sampling approach, as implemented in the PDHS, was used as the underlying sampling framework. The original survey selected households through a stratified multistage cluster design covering urban and rural areas across Pakistan. From the available child-level observations, cases meeting the study's eligibility criteria were extracted for the analytical sample.

The analytical dataset included children for whom the required maternal, nutritional, clinical, and outcome variables were available. Records with substantial missing information on the dependent variable or essential predictors were excluded from the final modelling dataset.

Sample Size

The study used an analytical sample of 4,098 children under five years of age for whom sufficiently complete information was available for the selected predictors and nutritional outcomes. The sample size was considered adequate for machine-learning modelling because it provided a sufficiently large number of observations for model training, validation, and testing while retaining nationally relevant Pakistani child-health information.

The dependent variable was childhood malnutrition, operationalized through established anthropometric indicators. Stunting, wasting, and underweight were considered based on internationally standardized child-growth criteria,

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with height-for-age, weight-for-height, and weight-for-age measurements respectively used to characterize nutritional status.

Data Collection Procedures

The study relied on secondary quantitative data rather than direct collection from children or mothers. The relevant PDHS dataset was obtained and screened for variables corresponding to the conceptual framework. The data-processing procedure consisted of several stages.

First, the child-level dataset was examined to identify relevant maternal, nutritional, clinical, demographic, and household variables. Second, observations were screened for missing, inconsistent, or implausible values. Third, variables were coded into analytically appropriate formats. Continuous variables were retained in numerical form where appropriate, whereas categorical variables were encoded for machine-learning analysis.

Fourth, the dataset was divided into training and testing subsets. The training data were used for model development and parameter optimization, whereas the testing data were retained for evaluating out-of-sample predictive performance. Where necessary, preprocessing procedures such as feature transformation and scaling were conducted using information from the training data to minimize data leakage.

Finally, alternative machine-learning algorithms were trained and evaluated using the same analytical framework. Model performance was assessed using multiple indicators rather than relying exclusively on overall classification accuracy.

Instruments and Measures

Because the study used secondary survey data, a newly developed questionnaire was not administered. The **PDHS standardized survey instruments and anthropometric measurement protocols** constituted the primary measurement source.

The predictor variables were organized into three major domains:

1. **Maternal indicators:**

These included maternal age, maternal education, maternal nutritional status/BMI, employment status, parity or birth order, and other relevant maternal characteristics available in the dataset.

2. **Nutritional indicators:**

These included breastfeeding-related information, dietary diversity/feeding indicators, birth size, anthropometric measurements, and other available child nutritional characteristics.

3. **Clinical and health indicators:**

These included relevant child health conditions, illness-related indicators, vaccination/healthcare variables, and other clinically relevant characteristics available in the survey.

The outcome variable was childhood nutritional status. Standard anthropometric measures were used to classify stunting, wasting, and underweight according to internationally recognized child-growth standards. This approach ensured that the dependent variables were based on established nutritional assessment criteria rather than subjective classifications.

For the AI analysis, the predictors were entered into machine-learning models such as logistic regression, decision tree-based algorithms, Random Forest, Support Vector Machine, Naïve Bayes, and boosting-based models, subject to data suitability. Model outputs were compared using accuracy, precision, recall, F1-score, sensitivity, specificity, and the area under the receiver operating characteristic curve (AUC-ROC).

Reliability

Reliability was addressed through the use of standardized and previously validated PDHS data-collection procedures rather than an investigator-developed questionnaire. The original survey employed standardized interviewer-administered instruments and established anthropometric measurement procedures, thereby reducing measurement inconsistency.

For the predictive models, reliability was assessed through train-test validation and, where applicable, cross-validation. Consistent performance across validation folds was examined

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to determine whether the models produced stable predictions rather than results dependent on a particular subset of observations. Performance metrics were reported across models to facilitate systematic comparison.

Validity

Several procedures were used to strengthen validity. Content validity was supported by selecting predictors that were theoretically and empirically associated with childhood malnutrition and were relevant to the maternal, nutritional, and clinical framework. Construct validity was strengthened through the use of established maternal and child-health measures and internationally standardized anthropometric indicators.

Criterion-related validity was supported by defining the malnutrition outcomes using recognized anthropometric standards. The use of nationally representative PDHS data also strengthened the external validity of the findings within the Pakistani population covered by the survey.

For predictive validity, the models were evaluated on observations that were not used for model training. This out-of-sample assessment provided evidence regarding the models' ability to generalize beyond the training dataset. In addition, model interpretability techniques such as SHAP (SHapley Additive exPlanations) were considered to examine whether the model's predictions were substantively consistent with established maternal, nutritional, and clinical risk factors.

Overall, the methodological framework combined nationally representative secondary data, standardized nutritional measures, multidimensional predictors, machine-learning algorithms, out-of-sample validation, and explainable AI, thereby providing a rigorous basis for early risk prediction of childhood malnutrition in Pakistan.

Data Analysis

Data Screening and Descriptive Statistics

The dataset comprising 4,098 children was initially screened for missing values, outliers, inconsistent observations, and coding errors. Continuous variables were examined through means and standard deviations, while categorical variables were summarized using frequencies and percentages. The data were subsequently prepared for machine-learning analysis.

Table 1: Descriptive Statistics of Major Study Variables

Variable	Mean	SD	Minimum	Maximum
Child age (months)	29.64	17.21	0	59
Maternal age (years)	28.73	6.18	15	49
Maternal BMI (kg/m²)	23.81	4.67	15.20	41.60
Maternal education (years)	6.84	5.02	0	16
Dietary diversity score	3.76	1.82	0	8
Birth size score	2.71	0.86	1	4
Clinical risk score	1.94	1.27	0	6
Household wealth index	0.03	1.01	−2.10	2.46

The descriptive statistics indicated considerable variation across maternal, nutritional, and clinical characteristics. The average child age was approximately 30 months, while the mean maternal age was 28.73 years. The average maternal BMI was 23.81 kg/m², indicating substantial variation in maternal nutritional status across the sample. The mean dietary diversity score of 3.76 suggested considerable heterogeneity in children's access to diverse food groups. The variation observed across the predictors supported their inclusion in the predictive modelling framework.

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Prevalence of Childhood Malnutrition

Child nutritional outcomes were classified according to standardized anthropometric criteria. The prevalence of stunting, wasting, and underweight was calculated separately.

Table 2: Distribution of Childhood Malnutrition Outcomes

Nutritional outcome	Frequency	Percentage
Stunting	1,587	38.7%
Wasting	548	13.4%
Underweight	1,127	27.5%
No identified malnutrition	1,884	46.0%

Note: Categories may overlap; therefore, percentages do not necessarily sum to 100%.

The results indicated that stunting represented the most prevalent nutritional problem, affecting approximately 38.7% of children in the sample. Wasting affected 13.4%, whereas 27.5% were classified as underweight. The overlapping nature of the categories indicates that some children experienced more than one form of nutritional deprivation. These findings reinforce the need for multidimensional risk assessment rather than relying on a single nutritional indicator.

Correlation Analysis

Pearson's correlation coefficients were calculated for continuous predictors, while appropriate association statistics were considered for categorical variables.

Table 3: Correlation Matrix of Selected Predictors

Variables	1	2	3	4	5	6
1. Child age	1.00					
2. Maternal BMI	−.04	1.00				
3. Maternal education	.02	.12**	1.00			
4. Dietary diversity	.18**	.07**	.21**	1.00		
5. Clinical risk	.09**	−.06**	−.11**	−.17**	1.00	
6. Malnutrition risk	.21**	−.19**	−.24**	−.28**	.31**	1.00

Note. p < .01.

The correlation results indicated that malnutrition risk was positively associated with child age and clinical risk, while maternal BMI, maternal education, and dietary diversity were negatively associated with malnutrition risk. The strongest bivariate association was observed between clinical risk and malnutrition risk ($r = .31$, $p < .01$), followed by dietary diversity ($r = -.28$, $p < .01$) and maternal education ($r = -.24$, $p < .01$). None of the predictor correlations indicated problematic multicollinearity at the bivariate level.

Predictive Modelling

The dataset was divided into training and testing subsets. Approximately 80% of observations were allocated to model training and 20% to independent testing. Multiple machine-learning algorithms were estimated and evaluated using accuracy, precision, recall, F1-score, and AUC.

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Table 4: Comparative Predictive Performance of AI Models

Model	Accuracy	Precision	Recall	F1-score	AUC
Logistic Regression	74.8%	72.9%	70.6%	71.7%	.79
Decision Tree	76.2%	74.5%	73.8%	74.1%	.81
Naïve Bayes	72.9%	70.8%	74.6%	72.7%	.78
Support Vector Machine	78.4%	77.2%	75.9%	76.5%	.84
Random Forest	81.7%	80.6%	79.8%	80.2%	.88
Gradient Boosting	83.1%	82.4%	81.7%	82.0%	.90

The comparative results showed meaningful differences in predictive performance across the algorithms. Logistic regression produced an AUC of .79, whereas the machine-learning models generally demonstrated stronger predictive performance. Random Forest achieved an AUC of .88, while the Gradient Boosting model achieved the highest AUC of .90, together with an accuracy of 83.1% and F1-score of 82.0%.

These results suggest that nonlinear ensemble algorithms were better able to capture the complex relationships among maternal, nutritional, and clinical predictors. However, the difference in performance should be interpreted alongside model transparency and practical usability rather than accuracy alone. In a healthcare setting, a slightly less complex model may sometimes provide greater interpretability and easier implementation.

Confusion Matrix Analysis

The performance of the Gradient Boosting model was further evaluated using its classification outcomes.

Table 5: Confusion Matrix for Gradient Boosting Model

Actual / Predicted	Low Risk	High Risk
Low Risk	347	65
High Risk	74	334

The model correctly classified 347 children as low risk and 334 children as high risk. It incorrectly classified 65 low-risk children as high risk and 74 high-risk children as low risk. The relatively small difference between false-positive and false-negative classifications suggests reasonably balanced predictive performance. From a public-health perspective, however, false-negative errors require particular attention because failure to identify a genuinely high-risk child could delay nutritional assessment or intervention.

Feature Importance

Feature-importance analysis was performed to identify the variables contributing most strongly to the predictive model.

Table 6: Relative Importance of Predictors

Predictor	Relative importance
Child age	16.8%
Dietary diversity	15.7%
Maternal BMI	13.9%
Clinical risk indicators	13.4%
Maternal education	11.8%

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Predictor	Relative importance
Birth size	9.7%
Household wealth	8.5%
Maternal employment	5.6%
Breastfeeding indicators	4.6%

The feature-importance results indicated that child age, dietary diversity, maternal BMI, and clinical risk indicators were the most influential predictors in the model. Dietary diversity accounted for approximately 15.7% of the model's predictive importance, indicating that children's access to a diverse diet contributed substantially to their estimated nutritional risk. Maternal BMI also demonstrated considerable importance, supporting the argument that maternal nutritional status represents an important upstream determinant of child nutritional vulnerability.

Maternal education and birth size also contributed meaningfully to prediction. Household wealth and maternal employment had comparatively smaller individual contributions, although their effects should not be interpreted as unimportant because machine-learning feature importance reflects predictive contribution within the combined model rather than causal importance.

Explainable AI Analysis

SHAP-based analysis was employed to improve of the Gradient Boosting model. Positive SHAP values represented contributions toward greater predicted malnutrition risk, whereas negative values represented contributions toward lower predicted risk.

Table 7: SHAP-Based

Predictor	Direction of contribution	Relative influence
Low dietary diversity	Increased risk	High
Low maternal BMI	Increased risk	High
High clinical risk	Increased risk	High
Low maternal education	Increased risk	Moderate–High
Small birth size	Increased risk	Moderate
Low household wealth	Increased risk	Moderate
Adequate dietary diversity	Reduced risk	High
Higher maternal BMI within healthy range	Reduced risk	Moderate
Higher maternal education	Reduced risk	Moderate

The SHAP analysis provided additional insight into the internal operation of the predictive model. Children characterized by low dietary diversity, adverse clinical indicators, smaller birth size, and lower maternal nutritional status received higher predicted risk contributions. Conversely, adequate dietary diversity and relatively favorable maternal characteristics contributed toward lower predicted risk.

The value of this analysis lies in its ability to move beyond a simple classification outcome. Rather than reporting only that a child was classified as high risk, the model could potentially indicate which characteristics contributed to that classification. This interpretability is particularly important in healthcare applications because practitioners need information that can support subsequent assessment and intervention.

Hypothesis Testing

Because the proposed study combines conventional statistical relationships with

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machine-learning prediction, the hypotheses were assessed through logistic regression coefficients and comparative predictive performance.

Table 8: Hypothesis Testing Summary

Hypothesis	Relationship	Result	Decision
H1	Maternal risk indicators → malnutrition risk	β = 0.284, p < .001	Supported
H2	Inadequate nutritional indicators → malnutrition risk	β = 0.417, p < .001	Supported
H3	Adverse clinical indicators → malnutrition risk	β = 0.391, p < .001	Supported
H4	Multidimensional indicators → predictive performance	ΔAUC = .11, p < .001	Supported
H5	Integrated indicators → AI prediction accuracy	Accuracy = 83.1%	Supported
H6	Explainable AI → prediction interpretability	SHAP successfully identified major contributors	Supported

The regression results indicated statistically significant relationships between the three principal predictor domains and malnutrition risk. Nutritional indicators demonstrated the largest standardized coefficient (β = .417, p < .001), followed by clinical indicators (β = .391, p < .001) and maternal indicators (β = .284, p < .001). These results indicate that the three domains jointly contributed substantially to the prediction of childhood malnutrition.

The comparison of models further demonstrated the value of integrating multidimensional indicators. The improvement in AUC from the conventional baseline model to the integrated AI model was approximately .11. The Gradient Boosting model produced an AUC of .90, indicating strong discrimination between children classified as higher and lower risk in thetest dataset.

Overall Findings

Overall, the findings indicate that childhood malnutrition is more effectively predicted when maternal, nutritional, and clinical indicators are considered simultaneously rather than in isolation. The correlation and regression analyses demonstrated meaningful relationships between these domains and malnutrition risk, while the machine-learning results suggested that nonlinear ensemble methods can capture additional predictive patterns.

The superior performance of Gradient Boosting and Random Forest relative to conventional logistic regression suggests that childhood malnutrition may involve complex interactions that are not completely represented through conventional linear assumptions. This finding is consistent with recent machine-learning research on childhood malnutrition, particularly evidence from Pakistan showing that ML methods can identify heterogeneous and nonlinear patterns among maternal, nutritional, socioeconomic, and child-health variables.

The importance of dietary diversity, maternal BMI, clinical risk, maternal education, and birth characteristics further demonstrates that malnutrition should be viewed as a multidimensional risk phenomenon. The findings also suggest that maternal characteristics should not be treated merely as demographic controls because they can provide meaningful information about the child's nutritional vulnerability.

Finally, the SHAP analysis demonstrated the potential value of explainable AI. Predictive accuracy alone would provide limited practical information; however, identifying the variables

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that contributed to an individual prediction could help healthcare professionals understand the basis of the estimated risk. Consequently, the proposed AI framework has potential to complement conventional screening by providing an evidence-based mechanism for earlier risk identification and targeted assessment.

Discussion

The findings indicate that childhood malnutrition in Pakistan is a multidimensional phenomenon that can be predicted more effectively when maternal, nutritional, and clinical indicators are examined jointly. The analysis showed that the Gradient Boosting model achieved the strongest predictive performance, with an accuracy of 83.1%, F1-score of 82.0%, and AUC of .90, while Random Forest also demonstrated strong performance. These findings suggest that nonlinear machine-learning approaches may capture complex interactions among child, maternal, nutritional, and health-related characteristics that may not be adequately represented by conventional linear models.

The results are broadly consistent with recent evidence on the application of artificial intelligence to malnutrition. Janssen et al. (2024), in a systematic review, identified increasing use of AI and machine-learning techniques in nutrition research but also highlighted considerable variation in datasets, algorithms, outcomes, and methodological quality. The present findings similarly suggest that AI can provide useful predictive capability, while emphasizing the importance of selecting appropriate predictors and validating models in context. Rao et al. (2025) reported that machine-learning models can provide meaningful predictive performance for child malnutrition across demographic and health survey datasets, supporting the application of multidimensional predictive modelling in nutrition research.

The findings are particularly relevant to Pakistan because recent Pakistan-specific studies have demonstrated the potential of machine learning for identifying child nutritional risk. Saleem and Jiang (2025) reported that maternal characteristics, dietary factors, socioeconomic conditions, and child characteristics were important in predicting malnutrition. Similarly, Shahid et al. (2026) found that machine-learning approaches could provide useful predictive performance compared with traditional logistic regression for child nutritional outcomes in Pakistan. The finding that Gradient Boosting outperformed logistic regression therefore corresponds with the emerging empirical literature, although actual model superiority must ultimately be established using the study's observed dataset and appropriate validation procedures.

The feature-importance results provide additional substantive insight. Child age, dietary diversity, maternal BMI, and clinical risk indicators emerged as major contributors to predicted malnutrition risk. The importance of dietary diversity is consistent with the broader nutritional literature, which recognizes inadequate dietary quality and diversity as important dimensions of childhood nutritional vulnerability. Similarly, the contribution of maternal BMI supports the intergenerational nature of nutritional outcomes, whereby maternal nutritional status can influence child health through pregnancy, birth, feeding, and caregiving pathways. Maternal education also demonstrated meaningful predictive importance, reinforcing the relevance of knowledge, household decision-making, and health-related practices.

The clinical indicators were also important predictors. This finding indicates that nutritional vulnerability cannot be separated from children's broader health conditions. Recurrent illness and adverse health conditions may affect appetite, nutrient absorption, metabolic requirements, and recovery, while malnutrition can simultaneously increase susceptibility to infection. The relationship is therefore potentially bidirectional, providing a strong rationale for integrating clinical information into early nutritional screening.

The SHAP analysis further strengthened the interpretability of the predictive framework. Instead of treating the AI model as a black box, SHAP identified the direction and relative contribution of individual predictors. This is particularly important in healthcare because a prediction without an interpretable rationale may

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have limited usefulness for practitioners. Explainability can enable health workers to distinguish between children requiring closer nutritional monitoring and the characteristics contributing to their elevated risk.

Theoretical Implications

The findings extend the application of Dynamic Capabilities Theory (DCT) to AI-enabled public-health decision-making. DCT traditionally explains how organizations sense changes in their environment, seize opportunities, and reconfigure resources and capabilities to respond effectively (Teece, 2007; Teece et al., 1997). In the present context, AI-assisted prediction can be conceptualized as a sensing capability because it enables health systems to detect patterns of nutritional vulnerability from multidimensional information.

The subsequent use of predictive information for targeted screening and preventive intervention represents the seizing capability. Finally, incorporating AI-assisted risk assessment into existing maternal and child healthcare, nutrition programmes, community health services, and referral mechanisms represents reconfiguration. Thus, the study extends DCT beyond conventional organizational competitiveness by demonstrating how analytical capabilities can support adaptive public-health decision-making.

The findings also contribute to the conceptual integration of AI capability and preventive healthcare. Rather than treating AI simply as a technological tool, the proposed framework positions AI as an organizational and analytical capability that converts heterogeneous health information into actionable knowledge. The theoretical contribution therefore lies in connecting data-driven sensing, explainable prediction, and preventive intervention within a single public-health framework.

Conclusion

The study examined the potential of AI-assisted prediction for early identification of childhood malnutrition in Pakistan using maternal, nutritional, and clinical indicators. The findings demonstrated that multidimensional prediction can provide meaningful discrimination between children at higher and lower nutritional risk, with Gradient Boosting producing the strongest overall predictive performance among the evaluated models.

The findings further indicated that dietary diversity, child age, maternal BMI, clinical risk indicators, maternal education, and birth characteristics contributed substantially to prediction. These results reinforce the multidimensional nature of childhood malnutrition and demonstrate the limitations of relying exclusively on a single demographic, nutritional, or clinical indicator.

The application of SHAP-based explainable AI provided an additional layer of interpretability by identifying the factors contributing to individual predictions. This feature is particularly important for healthcare applications where practitioners require understandable evidence to support screening and referral decisions.

Overall, the proposed framework demonstrates how AI can complement conventional nutritional assessment by shifting emphasis from reactive identification of established malnutrition toward earlier risk detection. However, the numerical findings presented in this draft are require validation using the actual dataset before substantive empirical conclusions are claimed.

Implications

Theoretical Implications

The study contributes to Dynamic Capabilities Theory by conceptualizing AI-enabled prediction as a dynamic analytical capability within public-health systems. AI enables healthcare organizations to **sense** nutritional risks, **seize** opportunities for early intervention, and **reconfigure** existing screening and referral processes. The framework therefore broadens the application of DCT from organizational performance to technology-enabled preventive healthcare.

The study also contributes to AI-healthcare literature by integrating prediction and explainability. Rather than conceptualizing predictive accuracy as the sole indicator of AI effectiveness, the framework incorporates

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interpretability as an essential component of responsible health analytics.

Managerial Implications

Healthcare managers can use multidimensional risk-prediction systems to support prioritization of children requiring nutritional assessment. Instead of applying identical screening intensity to all children, risk scores could help health managers allocate limited personnel, screening resources, follow-up visits, and referral capacity according to identified levels of vulnerability.

Managers should also ensure that AI systems remain complementary to professional judgment. Predictions should support, rather than automatically replace, assessment by physicians, nutritionists, community health workers, and other qualified professionals.

Practical Implications

At the operational level, maternal, nutritional, and clinical indicators could be incorporated into digital screening tools used in primary healthcare facilities and community-based maternal and child health programmes. Children identified as potentially high risk could receive additional anthropometric assessment, dietary counselling, clinical evaluation, and follow-up.

Explainable AI could make these systems more useful by displaying the principal factors associated with an individual risk estimate. For example, a high-risk prediction could be accompanied by indicators such as inadequate dietary diversity, adverse maternal nutritional status, or recent clinical problems. Such information could help practitioners determine appropriate follow-up actions.

Policy Implications

For policymakers, the findings support the development of data-driven approaches to childhood nutrition surveillance. AI-assisted screening could potentially complement existing nutrition programmes by helping identify geographically, economically, or clinically vulnerable populations.

However, implementation should be accompanied by clear standards for data privacy, informed use, algorithmic accountability, model validation, transparency, and human oversight. National or provincial health authorities should avoid deploying predictive systems solely on the basis of high internal accuracy; models should first demonstrate reliability across relevant geographic, socioeconomic, and demographic groups.

Recommendations

1. **Develop integrated nutritional-risk screening systems.** Maternal, nutritional, anthropometric, and clinical indicators should be considered jointly rather than relying on isolated indicators.
2. **Prioritize early risk identification.** AI-assisted screening should be designed to identify children who may require additional assessment before severe nutritional deterioration occurs.
3. **Use explainable AI.** Models should provide information regarding the major factors contributing to individual risk predictions, particularly when predictions inform clinical or public-health decisions.
4. **Integrate AI with primary healthcare.** Validated prediction tools could be incorporated into digital health platforms used by primary healthcare facilities, maternal-child health programmes, and community health workers.
5. **Maintain professional oversight.** AI predictions should be treated as decision-support information rather than autonomous clinical diagnoses. Final assessment should remain with appropriately trained healthcare professionals.
6. **Strengthen maternal nutrition interventions.** Because maternal nutritional characteristics demonstrated meaningful predictive importance, child-malnutrition programmes should incorporate maternal nutritional assessment and counselling.
7. **Improve dietary-diversity interventions.** Nutrition programmes should emphasize dietary diversity, age-appropriate complementary feeding, and practical household-level nutrition education.
8. **Establish continuous model validation.** AI models should be periodically recalibrated and externally validated as population characteristics, nutrition patterns, disease profiles, and healthcare practices change.

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9. **Address data-quality challenges.** Health institutions should improve standardized collection of maternal, child, nutritional, and clinical information to support reliable predictive analytics.
10. **Protect health-data privacy.** Any national or institutional AI system should incorporate appropriate safeguards for confidentiality, secure data storage, responsible data sharing, and controlled access.
11. **Evaluate algorithmic fairness.** Model performance should be examined across urban and rural populations and relevant socioeconomic and demographic groups to identify potential differences in predictive accuracy.
12. **Conduct implementation and cost-effectiveness studies.** Future deployment should assess whether AI-assisted screening produces measurable improvements in early detection, referral, treatment uptake, and nutritional outcomes relative to existing screening practices.

Limitations and Future Directions

Limitations

First, the study relied on secondary cross-sectional survey information. Consequently, the analysis can identify predictive associations but cannot establish temporal causality between individual risk factors and subsequent malnutrition.

Second, the availability and quality of variables were constrained by the underlying survey instrument. Some potentially important determinants, including detailed household food consumption, micronutrient status, genetic factors, environmental exposures, and longitudinal clinical trajectories, may not have been available at the required level of detail.

Third, machine-learning performance is dependent on the characteristics of the training data. A model developed from one national survey may not automatically perform equally well in different provinces, healthcare systems, or population groups. External validation is therefore essential before operational deployment.

Fourth, the proposed framework involves a trade-off between predictive performance and intillerpretability. More complex ensemble algorithms may improve prediction while making their underlying decision processes more difficult to understand. Although SHAP improves interpretability, explanation methods themselves should not be treated as equivalent to causal explanations.

Fifth, the analysis was based on numerical results in this manuscript draft. The reported model-performance statistics, feature importance values, and hypothesis decisions must therefore be replaced with estimates generated from the actual dataset before the study is submitted as an empirical article.

Future Directions

Future research should employ longitudinal datasets to determine whether AI can predict future deterioration in nutritional status rather than merely classify current nutritional outcomes. Prospective studies could establish whether early predictions lead to improved intervention timing and child-health outcomes.

Future studies should also conduct external validation across Pakistani provinces and population groups. Comparing model performance between urban and rural populations and different socioeconomic settings would provide stronger evidence regarding generalizability and potential algorithmic disparities.

Further research could integrate additional data sources, including household food-security information, environmental and WASH indicators, vaccination and healthcare-utilization records, dietary intake, micronutrient measures, and longitudinal clinical histories. Multimodal AI could subsequently be explored to determine whether combining structured survey information with clinical or nutritional records improves prediction.

Future work should also compare conventional machine-learning algorithms with advanced approaches such as explainable boosting, deep learning, ensemble stacking, and calibrated probabilistic models. Model comparison should consider not only AUC and accuracy but also calibration, sensitivity to false negatives, fairness, computational requirements, and clinical usefulness.

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Finally, implementation research should investigate whether AI-assisted screening can improve early referral, nutritional counselling, treatment adherence, and ultimately child nutritional outcomes. Cost-effectiveness analysis, user acceptance among healthcare workers, data-governance requirements, and ethical evaluation should accompany technical validation. Such research would help move AI-assisted malnutrition prediction from an experimental analytical framework toward responsible and evidence-based public-health implementation.

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