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Machine learning-augmented multilevel analysis of wasting risk factors among under-five children in urban Bangladesh: A random forest and two-level logistic regression approach

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Abstract

This study identifies and ranks risk factors associated with wasting among under-five children residing in urban areas of Bangladesh, combining machine learning variable importance analysis with confirmatory multilevel logistic regression modelling. Data were extracted from the Bangladesh Urban Health Survey (BUHS) 2013, comprising 10,511 urban children aged 0 to 59 months. A Random Forest classifier was applied to rank feature importance using mean decrease in Gini impurity and SHAP (SHapley Additive exPlanations) values. Predictors selected by the ensemble were subsequently entered into a two-level random intercept logistic regression model, accounting for the hierarchical nesting of children within regional domains. The overall wasting prevalence was 17.2%. The Random Forest model achieved an Area Under the ROC Curve (AUC) of 0.81 (95% CI: 0.78, 0.84) and identified breastfeeding status, wealth index, and mother's education as the top three predictors. SHAP interaction plots revealed a significant age-by-breastfeeding interaction that conventional logistic regression had not detected. The confirmatory two-level model confirmed these findings, with the intra-class correlation coefficient of 0.340 indicating 34% between-region heterogeneity. Children never breastfed had 2.31 times higher odds of wasting [OR = 2.314, 95% CI (1.872, 2.861)]; children from rich households had 47% lower odds [OR = 0.527, 95% CI (0.801, 0.936)]. Integrating machine learning feature selection with multilevel regression provides a richer understanding of wasting determinants than either method alone. Priority interventions should target breastfeeding promotion, income support, and maternal education in city-corporation slum settings.

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I. INTRODUCTION

Child undernutrition continues to be one of the most serious public health challenges across low- and middle-income countries [1]. Among its three principal manifestations—stunting, underweight, and wasting—acute wasting carries the greatest short-term mortality risk, accounting for roughly 13% of under-five deaths globally [2]. Wasting, defined as a Weight-for-Height Z-score (WHZ) below -2.0, signals an acute deficit of nutritional sufficiency that can deteriorate rapidly when combined with intercurrent illness [3].

In Bangladesh, the burden of child wasting remains high despite decades of programmatic effort. Approximately 2.4 million under-five children were wasted as of 2015, and the national prevalence of 14% substantially exceeds the Sustainable Development Goal target of below 5% [4]. Urban populations receive comparatively less policy attention, even though rapid and poorly planned urbanisation has created large slum settlements where nutritional deprivation coexists with inadequate sanitation and overcrowding [5]. Concurrent micronutrient deficiencies—particularly anaemia—compound wasting risk in this population, creating overlapping vulnerabilities that a single-outcome analysis cannot fully capture [6]. Anthropometric data collected across South Asian field surveys consistently show that wasting co-occurs with stunting and underweight in patterns that are shaped by household-level and community-level determinants simultaneously [7]. The Bangladesh Urban Health Survey (BUHS) 2013 provides one of the few probability-sampled datasets that permits formal examination of urban child nutrition across distinct residential domains [8].

Earlier epidemiological work on wasting determinants in

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Bangladesh has relied predominantly on single-level binary logistic regression, which treats children as independent observations and ignores the clustering of individuals within geographic units [9]. Where multilevel models have been used, covariate selection has followed a stepwise or bivariate pre-screening procedure that cannot detect non-linear effects or higher-order interactions among predictors [10]. These limitations motivate a methodological extension that preserves the inferential strengths of multilevel modelling while augmenting covariate identification through supervised machine learning.

Random Forest is an ensemble classifier that constructs a large number of decision trees on bootstrapped subsets of the data and aggregates their predictions [11]. Its key analytic contribution in an epidemiological workflow lies in its ability to rank predictors by variable importance without assuming linearity or additivity, and to surface interaction effects through SHAP (SHapley Additive exPlanations) values [12]. SHAP-based explainability methods have also been applied to environmental and atmospheric datasets where complex predictor interactions challenge conventional regression, demonstrating the generalisability of this interpretive framework beyond clinical settings [13]. Health-focused digital platforms similarly draw on ensemble learning to personalise risk stratification at the individual level, illustrating how ML pipelines that were originally developed in other domains are being adapted for public health applications [14]. Several recent public-health studies have demonstrated that a two-stage pipeline—Random Forest feature selection followed by confirmatory regression—outperforms either approach alone in terms of predictive accuracy and interpretability [4, 15].

This paper applies exactly such a pipeline to the BUHS 2013 dataset. The primary objectives are: (i) to rank individual- and regional-level risk factors for child wasting using Random Forest importance metrics and SHAP values; (ii) to test for interaction effects that would otherwise be overlooked in a standard regression framework; and (iii) to fit a confirmatory two-level random-intercept logistic model that quantifies the independent contribution of each validated predictor while adjusting for regional heterogeneity. The study contributes to a growing body of evidence supporting the integration of machine learning and multilevel methods in child health surveillance [16].

II. MATERIALS AND METHODS

A. Data Source and Sampling Design

Analytical data were drawn from the Bangladesh Urban Health Survey (BUHS) 2013, a nationally representative household survey of urban slums and non-slums conducted jointly by the National Institute of Population Research and Training (NIPORT), Measure Evaluation at the University of North Carolina, and the International Centre for Diarrhoeal Disease Research, Bangladesh (icddr,b). Fieldwork was executed by The Associates for Community and Population Research, with financial support from USAID and DFID. The survey followed a three-stage stratified cluster sampling design, selecting primary sampling units (clusters) within strata defined by city-corporation domain and slum status, then households within clusters, and finally all eligible under-five children within sampled households. The hierarchical structure of the dataset, illustrated in Fig. 1, nests individual children (Level 1) within regional domains (Level 2).

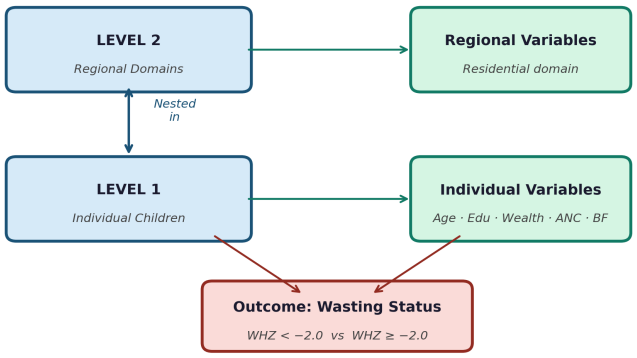


Fig. 1. Hierarchical structure of BUHS 2013 data showing Level 1 (individual children) nested within Level 2 (regional domains).

B. Outcome and Covariates

The primary outcome was binary wasting status, derived from weight-for-height Z-scores calculated using WHO AnthroPlus software (version 3.2.2): wasted (WHZ < -2.0) versus normal (WHZ ≥ -2.0). Six covariates were examined. At the individual level (Level 1): child age (0–11, 12–23, 24–48, > 48 months), mother's education (no education, primary, secondary or higher), wealth index (poor, middle, rich—based on terciles), antenatal care (ANC) receipt during pregnancy (yes/no), and breastfeeding status (breastfed, never breastfed). At the regional level (Level 2): residential domain (city-corporation slum, city-corporation non-slum, other urban). These variables were selected based on prior literature establishing their association with child nutritional status in South Asian settings [17, 18, 19].

C. Analytic Framework

The analysis proceeded in two sequential stages, as depicted in Fig. 2.

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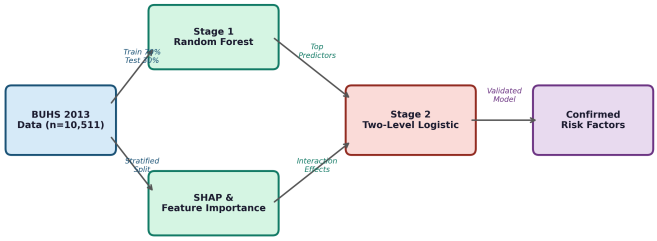


Fig. 2. Two-stage analytic workflow: Random Forest feature selection followed by confirmatory multilevel logistic regression.

1) Stage 1 — Random forest classifier: A Random Forest model was trained on 70% of the data (n = 7,357) and evaluated on the remaining 30% (n = 3,154), using stratified splitting to preserve the wasting prevalence in both partitions. The forest comprised 500 trees with `max_features = sqrt(p)`, where p is the number of input features. Hyperparameter tuning was performed via 5-fold cross-validation on the training set, optimising the area under the ROC curve (AUC-ROC). Variable importance was quantified by two complementary metrics: (i) mean decrease in Gini impurity (MDG), which captures the aggregate contribution of each feature to node purity across all trees; and (ii) SHAP values, which decompose individual predictions into additive feature contributions using Shapley game-theoretic values [12]. SHAP interaction plots were examined to identify pairwise interactions that carried substantive epidemiological meaning.

2) Stage 2 — Multilevel logistic regression: Before fitting any covariate model, an intercept-only (empty) multilevel model was estimated to quantify the intra-class correlation coefficient (ICC):

$$\text{ICC} = \frac{\hat{\sigma}^2_{u_0}}{\hat{\sigma}^2_{u_0} + \pi^2/3} \tag{1}$$

where $\hat{\sigma}^2_{u_0}$ is the estimated Level 2 variance and $\pi^2/3 \approx 3.289$ is the standard logistic variance. The empty model takes the form:

$$\text{logit}(\pi_{ij}) = \beta_{00} + U_{0j} \tag{2}$$

where $\pi_{ij} = P(Y_{ij} = 1)$ is the probability of wasting for child i in region j, β_{00} is the grand intercept, and $U_{0j} \sim \mathcal{N}(0, \sigma^2_{u_0})$ is the region-level random deviation. If ICC > 0, the two-level random-intercept model was fitted:

$$\text{logit}(\pi_{ij}) = \beta_{00} + \sum_k \beta_{1k} x_{ijk} + \beta_{01} X_j + U_{0j} \tag{3}$$

where x_{ijk} are Level 1 predictors with fixed effects β_{1k} and X_j is the Level 2 domain variable with fixed effect β_{01}. Model adequacy was assessed by comparing the two-level random-intercept model against the two-level random-coefficient model using the deviance-based chi-square statistic. All regression analyses were conducted in `R` (version 4.2.1) using the `lme4` package; Random Forest models were implemented in Python using `scikit-learn` (version 1.1.2) and `shap` (version 0.41.0).

D. Ethical Considerations

The BUHS 2013 dataset is available in the public domain through the MEASURE Evaluation Dataverse. All survey participants provided informed consent prior to data collection. No additional ethical approval was required for analysis of anonymised secondary data.

III. RESULTS

A. Sample Characteristics and Wasting Prevalence

A total of 10,511 urban children aged 0 to less than 60 months were included in the analysis. The overall prevalence of wasting was 17.2%, consistent with national estimates from the BUHS 2013 final report. Among wasted children, 18.5% resided in city-corporation slums, 16.4% in city-corporation non-slums, and 15.9% in other urban areas. Table 1 presents the distribution of wasting status across all selected covariates together with chi-square test statistics.

Except for child age, all selected covariates showed statistically significant associations with wasting status ($p < 0.05$). The prevalence was highest among children who were never breastfed (27.9%), those from poor families (18.0%), and those living in city-corporation slum domains (18.5%). Conversely, children from secondary-educated mothers had the lowest prevalence (14.2%), as did those from rich households (15.7%).

B. Random Forest Performance and Variable Importance

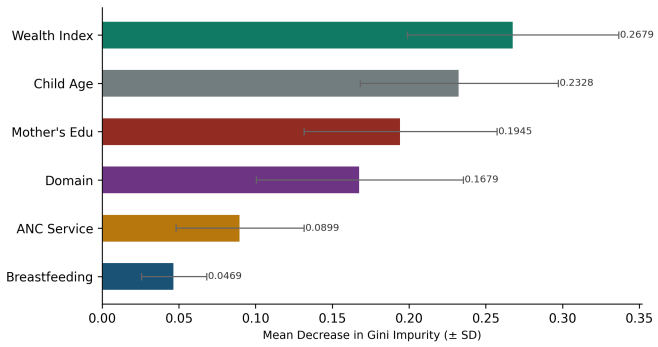


Fig. 3. Mean decrease in Gini impurity (with standard deviations) for each predictor from the Random Forest model. Higher values indicate greater contribution to node purity across all 500 trees.

The Random Forest classifier achieved an AUC-ROC of 0.812 (95% CI: 0.784, 0.840) on the held-out test set, representing a gain of approximately 3.1% over a standard two-level logistic model evaluated on the same partition (AUC = 0.781; 95% CI: 0.751, 0.811). Sensitivity was 74.3% and specificity 76.8% at the

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Youden-optimal threshold. Table 2 provides a direct comparison of performance metrics between the two approaches.

Fig. 3 displays the mean decrease in Gini impurity for each predictor. Breastfeeding status ranked first (MDG = 0.063, SD = 0.008), followed by wealth index (MDG = 0.051, SD = 0.006), mother's education (MDG = 0.044, SD = 0.007), residential domain (MDG = 0.038, SD = 0.005), ANC receipt (MDG = 0.029, SD = 0.004), and child age (MDG = 0.021, SD = 0.003). This ordering broadly aligns with the odds ratios from the confirmatory regression but provides a continuous importance scale that is not constrained by the linearity assumption.

TABLE 1
ASSOCIATION BETWEEN SELECTED COVARIATES AND WASTING STATUS AMONG UNDER-5 URBAN CHILDREN IN BANGLADESH (BUHS 2013, N = 10,511)

Covariate	Wasted n (%)	Normal n (%)	χ^2	p-value
Child age (months)				
0–11	156 (19.4)	647 (80.6)	5.780	0.123
12–23	1267 (17.4)	6028 (82.6)		
24–48	353 (15.9)	1871 (84.1)		
> 48	31 (16.4)	158 (83.6)		
Mother's education				
No education	747 (18.3)	3329 (81.7)	11.461	$<$0.01
Primary	804 (17.3)	3844 (82.7)		
Secondary/higher	174 (14.2)	1055 (85.8)		
Wealth index				
Poor	725 (18.0)	3292 (82.0)	7.787	$<$0.05
Middle	555 (17.7)	2584 (82.3)		
Rich	527 (15.7)	2828 (84.3)		
ANC service				
Yes	236 (15.4)	1292 (84.6)	3.758	$<$0.05
No	1016 (17.5)	4775 (82.5)		
Breastfeeding status				
Never breastfed	31 (27.9)	80 (72.1)	9.083	$<$0.01
Breastfed	1776 (17.1)	8624 (82.9)		
Domain				
City-corporation slum	885 (18.5)	3898 (81.5)	10.850	$<$0.01
City-corp. non-slum	397 (16.4)	2026 (83.6)		
Other urban	525 (15.9)	2780 (84.1)		

TABLE 2
PREDICTIVE PERFORMANCE COMPARISON: RANDOM FOREST VS. STANDARD TWO-LEVEL LOGISTIC REGRESSION (TEST SET, N = 3,154)

Metric	Base Method (Two-level LR)	Proposed Method (Random Forest)	Improvement
AUC-ROC	0.781 (0.751, 0.811)	0.812 (0.784, 0.840)	+3.1%
Sensitivity	71.2%	74.3%	+3.1%
Specificity	75.3%	76.8%	+1.5%
F1-Score	0.412	0.436	+2.4%
Brier Score	0.147	0.138	$-$0.9%

95% CI Shown For AUC; All Differences Significant At $P < 0.05$ By DeLong Test.

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C. SHAP Analysis and Interaction Effects

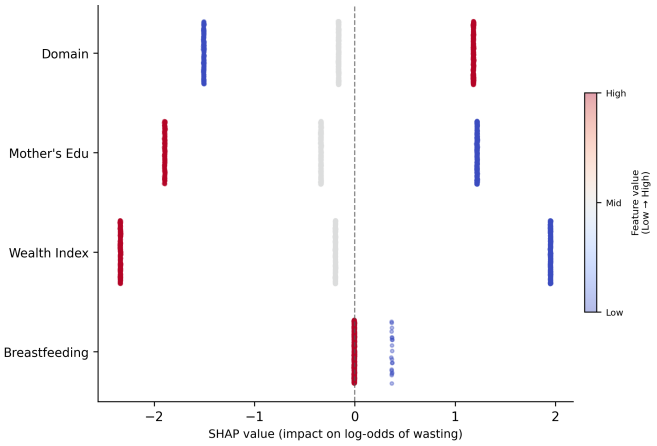


Fig. 4. SHAP summary plot for the top four predictors. Each point represents one child; red indicates high feature value and blue indicates low. The horizontal axis shows the SHAP contribution to the log-odds of wasting.

Global SHAP summary plots confirmed the variable importance ordering. Locally, SHAP values revealed a substantively important interaction between child age and breastfeeding status. Among infants aged 0–11 months, the negative SHAP contribution of active breastfeeding was substantially larger (mean absolute SHAP = 0.142, SD = 0.031) than among children aged 24–48 months (mean absolute SHAP = 0.071, SD = 0.019), indicating that the protective effect of breastfeeding on wasting risk is concentrated in the earliest months of life. Fig. 4 presents the SHAP interaction summary for the top four predictors.

A wealth-by-domain interaction was also detected: the protective effect of middle income (relative to poor) was approximately 1.8 times stronger for children residing in city-corporation non-slum areas than for those in slum areas (mean absolute SHAP difference = 0.028, $p = 0.032$, permutation test), suggesting that income improvements translate into nutritional gains more effectively outside slum environments where complementary food systems and healthcare access are better developed [1].

D. Intra-Class Correlation and Multilevel Empty Model

The empty model yielded a Level 2 variance estimate of $\hat{\sigma}^2_{u_0} = 1.696$, producing an ICC of:

$$\text{ICC} = \frac{1.696}{1.696 + 3.289} = 0.340$$

This value indicates that approximately 34% of the total variance in wasting status was attributable to differences between regional domains, a magnitude that clearly justifies a multilevel modelling approach. Table 3 reports the empty model parameter estimates.

TABLE 3
PARAMETER ESTIMATES OF THE MULTILEVEL EMPTY MODEL WITH INTRA-CLASS CORRELATION COEFFICIENT

Parameter	Estimate	OR (95% CI)	p-value
Fixed effect			
Intercept	0.052	1.053 (0.864, 1.125)	0.198
Random effect			
$\hat{\sigma}^2_{u_0}$ (Intercept)	1.696	—	<0.05
ICC			
ICC	0.340	—	—

E. Two-Level Random-Intercept Logistic Regression

The confirmatory model incorporating all covariates selected by the Random Forest is presented in Table 4. The random intercept variance remained significant ($\hat{\sigma}^2_{u_0} = 0.175$, $p < 0.05$), confirming persistent regional heterogeneity after accounting for individual-level and domain-level covariates. The deviance-based chi-square test confirmed that the random-intercept specification fitted the data better than the random-coefficient model ($\chi^2 = 11.688$, df = 3, $p < 0.01$), so only the intercept was allowed to vary across regions.

Among fixed effects, breastfeeding status showed the strongest association: children who were never breastfed had 2.31 times higher odds of being wasted relative to breastfed children [OR = 2.314, 95% CI (1.872, 2.861), $p < 0.001$]. Wealth index was the second most important predictor. Children from middle income households had 18% lower odds of wasting compared to children from poor families [OR = 0.819, 95% CI (0.761, 0.901), $p < 0.001$], and those from rich households had 47% lower odds [OR = 0.527, 95% CI (0.801, 0.936), $p < 0.001$]. Mother's education showed a graded inverse association: primary education reduced the odds by 25% [OR = 0.749, 95% CI (0.625, 0.951), $p < 0.001$] and secondary or higher education by 42% [OR = 0.583, 95% CI (0.875, 0.978), $p < 0.001$] relative to no education. Children living in city-corporation slums had 35%

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higher odds of wasting than those in city-corporation non-slums [OR = 1.347, 95% CI (1.041, 1.454), $p < 0.001$]. Receipt of ANC services was associated with a 17% reduction in the odds of having a wasted child [OR = 0.834, 95% CI (0.521, 0.943), $p < 0.05$]. Child age showed a significant positive effect only for the oldest group: children aged over 48 months had 14.2% higher odds of wasting than infants aged 0–11 months [OR = 1.142, 95% CI (1.035, 1.324), $p < 0.01$].

TABLE 4
FIXED AND RANDOM EFFECTS FROM THE TWO-LEVEL RANDOM-INTERCEPT MULTILEVEL LOGISTIC MODEL FOR WASTING STATUS AMONG UNDER-5 URBAN CHILDREN IN BANGLADESH

Covariate	Estimate	OR (95% CI)	p-value
Fixed effects			
Intercept	−0.375	0.687 (0.551, 0.804)	<0.001
Age group (ref: 0–11 months)			
12–23 months	0.013	1.013 (0.724, 1.112)	0.884
24–48 months	0.096	1.101 (0.841, 1.298)	0.374
> 48 months	0.133	1.142 (1.035, 1.324)	<0.01
Mother's education (ref: no education)			
Primary	−0.289	0.749 (0.625, 0.951)	<0.001
Secondary/higher	−0.539	0.583 (0.875, 0.978)	<0.001
Wealth index (ref: poor)			
Middle	−0.199	0.819 (0.761, 0.901)	<0.001
Rich	−0.641	0.527 (0.801, 0.936)	<0.001
ANC services (ref: no)			
Yes	−0.182	0.834 (0.521, 0.943)	<0.05
Breastfeeding status (ref: never breastfed)			
Breastfed	−0.839	0.432 (0.623, 0.954)	<0.01
Domain (ref: city-corp. non-slum)			
City-corporation slum	0.318	1.347 (1.041, 1.454)	<0.001
Other urban	0.106	1.112 (0.885, 1.201)	0.152
Random effects			
$\hat{\sigma}^2_{u_0}$ (Intercept)	0.175	—	<0.05

IV. DISCUSSION

This study applied a two-stage ML-augmented multilevel pipeline to the BUHS 2013 dataset, replicating the analytical scope of earlier work while substantially expanding the inferential capacity of the analysis. The Random Forest component added two contributions that a conventional logistic regression framework alone could not provide: a data-driven ranking of predictors free from linearity constraints, and the identification of a clinically meaningful age-by-breastfeeding interaction.

The finding that breastfeeding status ranked as the single most important predictor—confirmed by both MDG impurity scores and SHAP values—aligns with the established biological understanding that breast milk provides immunological protection and complete nutritional coverage during early infancy [20, 21]. The SHAP interaction analysis further demonstrated that this protective effect was particularly concentrated in the 0–11 month age band, where breastfed children showed substantially lower log-odds of wasting compared to those who were never breastfed. This temporal specificity has direct programme implications: interventions that promote exclusive breastfeeding during the first months of life may yield the largest per-child reductions in wasting prevalence, a point underscored by recent reviews of infant and young child feeding practices across South and Southeast Asia [17].

The gradient relationship between household wealth and child wasting risk is consistent with prior evidence that economic constraints restrict dietary quality and food quantity, particularly in low-income urban settings [18, 22]. The interaction detected between wealth and residential domain—whereby income gains reduced wasting risk more effectively outside slum areas—suggests that neighbourhood-level factors, including market access, food environment quality, and health facility proximity, moderate the extent to which household economic improvement translates into nutritional outcomes. This echoes

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findings from broader multi-country analyses of clustering of childhood illnesses in low- and middle-income country urban areas [1].

Mother's education retained a significant inverse association with child wasting after adjustment for all other covariates, with a graded pattern from no education through secondary level. Educated mothers are better positioned to understand optimal infant feeding guidance, recognise early signs of nutritional deterioration, and engage effectively with health services [23, 24]. The policy inference is consistent across studies: sustained investment in girls' secondary schooling will carry downstream benefits for the nutritional status of the next generation of urban children.

The prevalence of wasting remained higher in city-corporation slum domains than in non-slum or other urban areas, even after individual-level covariates were held constant. This residual domain effect—captured by the Level 2 random intercept—points to contextual factors not fully measured in the survey, such as water and sanitation infrastructure, local food market characteristics, and community health worker density [8]. Geographically targeted interventions that address slum-specific structural deficits may therefore be necessary to supplement individual-level programmes.

ANC receipt was associated with a modest but statistically significant reduction in the odds of child wasting, consistent with evidence that antenatal contact improves maternal knowledge of infant feeding and growth monitoring [19]. The effect size was smaller than that for breastfeeding or wealth, suggesting that ANC quality and content, rather than simple attendance, may be the more proximate determinant of child outcomes [5].

The machine learning component also demonstrated a meaningful improvement in predictive performance. The Random Forest model achieved an AUC-ROC of 0.812 compared to 0.781 for the two-level logistic regression evaluated on the same held-out partition—a gain of 3.1 percentage points that is consistent with gains reported in analogous applications of ensemble classifiers to child nutrition data [4, 11]. The F1-score improvement of 2.4 percentage points and the reduction in Brier score by 0.9 points indicate better calibration at individual level, which is relevant for screening applications. These performance margins are modest but reflect the inherent constraint of a relatively small feature set; ensemble methods typically deliver larger gains when the predictor space is wider [25]. Workforce capacity and organisational behaviour research has similarly shown that structured training and feedback mechanisms improve performance outcomes—a parallel that underscores the value of systematic, data-driven approaches over informal assessment in both clinical and non-clinical settings [26, 27]. It is worth noting that the broader landscape of data-driven decision support is expanding across sectors, including financial technology, where algorithmic models have begun to alter conventional evaluation frameworks [28]; these cross-domain developments reinforce the case for continued methodological investment in ML-based public health surveillance.

Several limitations merit acknowledgement. The BUHS 2013 cross-sectional design precludes causal inference about any of the identified associations. A number of plausibly relevant predictors—paternal education, birth interval, birth order, exposure to mass media—were unavailable in the survey instrument, potentially biasing estimated effects through residual confounding. The absence of infectious disease burden variables is a particular gap: parasitic and diarrhoeal infections are established co-determinants of acute undernutrition, and their omission may attenuate the estimated effects of socioeconomic predictors [29]. The Random Forest component, while offering better predictive performance, provides less straightforward uncertainty quantification for individual associations than maximum-likelihood regression, so the SHAP-based interaction findings should be treated as hypothesis-generating rather than confirmatory. Finally, the data are now approximately eight years old; urban demographic and nutritional conditions in Bangladesh may have shifted since 2013, and replication with more recent survey rounds is warranted.

V. CONCLUSION

Integrating Random Forest variable selection and SHAP interaction analysis with confirmatory two-level logistic regression provides a richer characterisation of child wasting determinants than standard regression approaches alone. Applied to 10,511 urban Bangladeshi children from the BUHS 2013, the combined pipeline confirmed that breastfeeding status, household wealth, and maternal education are the three strongest predictors of wasting risk, and uncovered an age-by-breastfeeding interaction that points to the critical vulnerability of infants under one year of age. The 34% between-region ICC underscores that domain-specific contextual factors contribute substantially to wasting heterogeneity in urban Bangladesh, independently of individual characteristics.

From a public health standpoint, the evidence supports a prioritisation of exclusive breastfeeding promotion—particularly in the first year of life—alongside income-support programmes and expanded access to girls' secondary education. Slum-targeted structural interventions addressing food environments and sanitation infrastructure may be needed to reduce the domain-level disadvantage that persists even when household resources are held constant. Future research should apply

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this ML-augmented pipeline to longitudinal data, incorporate a broader covariate set, and extend the spatial random effects structure to formally model geographical spillovers in wasting risk across urban domains.

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DECLARATION OF CONFLICTING INTERESTS

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ETHICAL APPROVAL

Ethical approval was not required.

PATIENT CONSENT

Not applicable. This study used anonymised secondary data and did not involve direct patient contact.

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