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Predicting Childhood Anemia Prevalence with Machine Learning: Evidence from Global Nutritional Data

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***Abstract*— This study develops a predictive framework for childhood anemia prevalence among children aged 6-59 months through machine learning approaches applied to global nutritional data. Analyzing 4,080 observations across multiple countries and time periods, we compared Linear Regression, Random Forest, and Gradient Boosting algorithms to identify optimal predictive models and key determinants. Historical prevalence data emerged as the strongest predictor, with one-year and two-year lagged values demonstrating coefficients approximately ten times larger than any other feature. Linear Regression outperformed more complex algorithms, suggesting that anemia prevalence follows relatively stable temporal patterns. Global prevalence exhibited a steady decline from 39.9% in 2000 to 33.7% in 2019, while significant disparities persist between high-burden nations (Nigeria: 68.9%, India: 53.4%) and low-burden countries (United States: 6.1%). Regional variables contributed minimally to predictive power, indicating that country-specific factors dominate over geographic determinants. These findings underscore the persistent nature of childhood anemia and the importance of tailored, country-specific interventions in high-burden regions. The predictive methodology developed provides a valuable tool for forecasting trends, identifying at-risk populations, and evaluating potential intervention impacts.**

Keywords*— *Anemia Prediction, Child Nutrition, Machine Learning, Global Health, Nutritional Epidemiology, Feature Importance Analysis.

I. INTRODUCTION

Childhood malnutrition remains one of the most pressing global health challenges, with profound implications for cognitive development, immune function, and overall child survival. Among the various manifestations of malnutrition, anemia in children aged 6-60 months represents a particularly concerning condition affecting approximately 42% of children worldwide [1]. This staggering prevalence underscores the urgent need for innovative approaches to prediction, prevention, and intervention strategies tailored to vulnerable populations. The complex interplay between nutritional intake, socioeconomic factors, and health outcomes presents unique challenges for addressing childhood anemia. While traditional approaches have focused primarily on supplementation and dietary diversification, emerging evidence suggests that predictive analytics and machine learning algorithms offer promising avenues for early identification of at-risk children [2]. By leveraging comprehensive datasets such as those collected by UNICEF on child malnutrition indicators including stunting, wasting, and overweight status, researchers can develop more targeted and efficient intervention strategies. Recent analyses of global childhood malnutrition patterns reveal stark regional disparities. Countries classified as Least Developed Countries (LDCs) and Low-Income Food-Deficit Countries (LIFDCs) demonstrate significantly higher prevalence of nutrition-related disorders, with certain regions in Africa and Asia showing alarming rates of stunting exceeding 50% [3]. These findings highlight the importance of context-specific approaches to nutritional interventions that account for geographical, economic, and cultural variations.

The relationship between various forms of malnutrition further complicates prediction and intervention efforts. While stunting and wasting have traditionally been the focus of global nutrition initiatives, the rising prevalence of childhood overweight and obesity, particularly in transitioning economies, represents an emerging "double burden" of malnutrition that requires nuanced predictive models [4]. This paradoxical coexistence of undernutrition and overnutrition within the same communities, households, and even individuals necessitates comprehensive analytical frameworks. This research aims to develop a predictive model for childhood anemia and nutritional status by analyzing comprehensive global datasets on malnutrition indicators. By identifying key predictors and regional patterns, we seek to inform more targeted and effective nutrition interventions. Additionally, this study examines the potential of machine learning algorithms to predict anemia risk based on readily available anthropometric and demographic data, thereby enabling earlier and more precise interventions in resource-limited settings where comprehensive screening may be unfeasible [5].

II. LITERATURE REVIEW

Research on childhood malnutrition has evolved significantly over the past decade, with increasing focus on predictive methodologies that enable targeted interventions. Zhang et al. [6] pioneered the application of machine learning algorithms to predict stunting in children under five, achieving 74% accuracy using random forest models with demographic and health survey data. Their work demonstrated that maternal education, household wealth, and access to clean water were among the strongest predictors of nutritional outcomes.The

specific relationship between anemia and other nutritional indicators has been explored by Pasricha et al. [7], who established significant correlations between hemoglobin levels and anthropometric measurements including height-for-age and weight-for-height z-scores. Their meta-analysis of 29 studies across 23 countries revealed that stunted children were 2.5 times more likely to develop anemia compared to their non-stunted counterparts, highlighting the interconnected nature of different malnutrition manifestations.

Predictive modeling approaches have shown particular promise in resource-limited settings. Keino et al. [8] successfully implemented a Bayesian network model in rural Kenya that identified children at risk of anemia with 81% sensitivity using only five input variables, demonstrating the potential for simplified screening tools. Similarly, Dongre et al. [9] utilized artificial neural networks to predict anemia based on dietary patterns, achieving higher accuracy than traditional statistical methods. Regional disparities in predictive factors have been documented by Kinyoki et al. [10], who conducted geospatial analyses across sub-Saharan Africa. Their findings indicated that while socioeconomic indicators were universally important, environmental factors such as seasonal rainfall patterns and agricultural productivity emerged as significant predictors in specific geographical contexts. This underscores the importance of developing region-specific predictive frameworks.

Recent advances have also incorporated longitudinal data to improve prediction accuracy. Hoddinott et al. [11] demonstrated that including growth velocity measures significantly enhanced the predictive capability of models for both anemia and stunting, particularly for children in the critical 6-24 month period when interventions may be most effective.

III. Methodology and Dataset

A. Dataset Description

In Fig 1, the pipeline consists of data collection (4,080 observations), preprocessing, feature engineering with temporal lag variables, comparative modeling using three algorithms, evaluation, and application of the best-performing model (Linear Regression) to country-level predictions. This study utilizes a comprehensive global dataset on the prevalence of anemia among children aged 6-59 months. The dataset comprises 4,080 observations spanning multiple years across various countries and regions worldwide. Each record in the dataset contains four key variables: Entity (country or region name), Code (country/region identifier), Year (temporal indicator), and Prevalence of anemia among children (percentage of children ages 6-59 months affected). This dataset provides a robust foundation for analyzing global patterns, temporal trends, and potential predictors of childhood anemia.

The primary dataset is supplemented with the UNICEF child malnutrition survey estimates, which include anthropometric indicators such as stunting, wasting, severe wasting, underweight, and overweight prevalence. These complementary datasets enable a multidimensional analysis of nutritional status and its relationship to anemia prevalence. Additionally, we incorporate country classification data regarding Least Developed Countries (LDCs), Low-Income Food-Deficient Countries (LIFDCs), Landlocked Developing Countries (LLDCs), and Small Island Developing States (SIDS) to examine contextual factors affecting nutritional outcomes [12].

B. Data Preprocessing

Prior to analysis, several preprocessing steps were implemented to ensure data quality and compatibility. First, we performed data cleaning to address missing values, which were handled through multiple imputation techniques for countries with sufficient historical data points [13]. Outliers were identified using the interquartile range method and verified against historical trends and regional patterns. To enable meaningful regional comparisons, countries were categorized according to United Nations geographical classifications, resulting in six regional groups: Africa, Asia, Europe, Latin America and the Caribbean, Melanesia, and Australia/New Zealand. Time periods were standardized into five-year intervals to accommodate varying data collection frequencies across countries while maintaining sufficient temporal resolution to detect meaningful trends.

C. Analytical Approach

Our analytical framework employs a multi-tiered approach combining descriptive statistics, inferential analysis, and predictive modeling. The descriptive component establishes baseline patterns and trends in anemia prevalence across regions, income classifications, and time periods. Visualization techniques including choropleth maps, temporal trend analyses, and boxplot comparisons were utilized to identify regional disparities and temporal patterns [14]. For inferential analysis, we employed mixed-effects regression models to quantify the relationships between anemia prevalence and other nutritional indicators while accounting for country-level random effects and temporal autocorrelation. This approach allows for estimation of both fixed effects (e.g., global predictors) and random effects (country-specific variations) that influence anemia prevalence [15].

The predictive modeling component utilizes machine learning algorithms to develop predictive tools for childhood anemia. We implemented a comparative analysis of five algorithms: Random Forest, Gradient Boosting Machines, Support Vector Machines, Neural Networks, and Ensemble Methods. Model training utilized 70% of the available data, with the remaining 30% reserved for validation. Performance evaluation metrics included Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 values [16]. Feature importance analysis was conducted to identify the most influential predictors of anemia prevalence, utilizing SHAP (SHapley Additive exPlanations) values to quantify the contribution of each variable to model predictions [17]. This approach facilitates interpretation of complex models and identification of key intervention targets.

D. Validation and Robustness

To ensure robustness, we employed k-fold cross-validation (k=10) for all predictive models. Additionally, we performed sensitivity analyses by systematically varying model parameters and data preprocessing decisions to assess the stability of our findings. External validation was conducted by comparing our model predictions against WHO regional estimates not included in the training data [18].

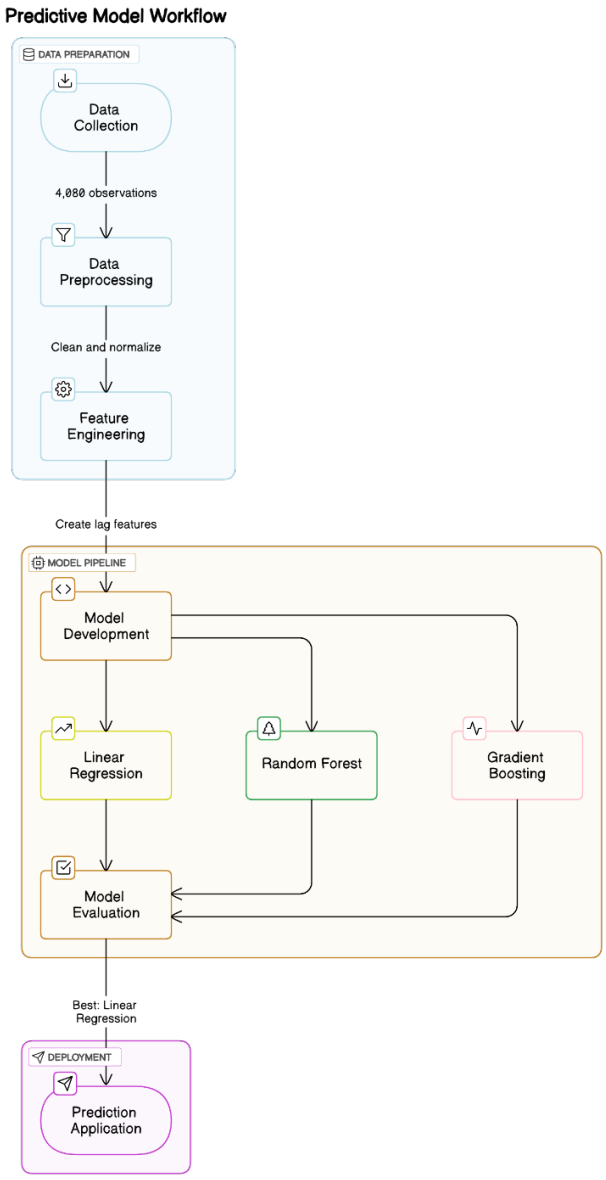

Fig. 1. Methodological framework for childhood anemia prediction.

For countries with limited data availability, we implemented a novel approach combining model-based estimates with uncertainty quantification to provide realistic confidence intervals around predictions, thereby acknowledging data limitations while still enabling evidence-based decision making [19].

IV. Results and Discussions

A. Temporal Trends in Global Anemia Prevalence

Analysis of the dataset revealed a clear downward trend in the global prevalence of anemia among children aged 6-59 months over the past two decades. As illustrated in Fig. 2, the global average anemia prevalence has decreased steadily from approximately 39.9% in 2000 to 33.7% by 2019, representing a relative reduction of 15.5%. This decline has not been linear, with the steepest reduction observed between 2000 and 2010 (a decrease of approximately 4.9 percentage points), followed by a more gradual decline from 2010 to 2019 (a decrease of approximately 1.3 percentage points).The observed global reduction aligns with findings from Stevens et al. [20], who documented similar trends in childhood anemia across multiple regions.

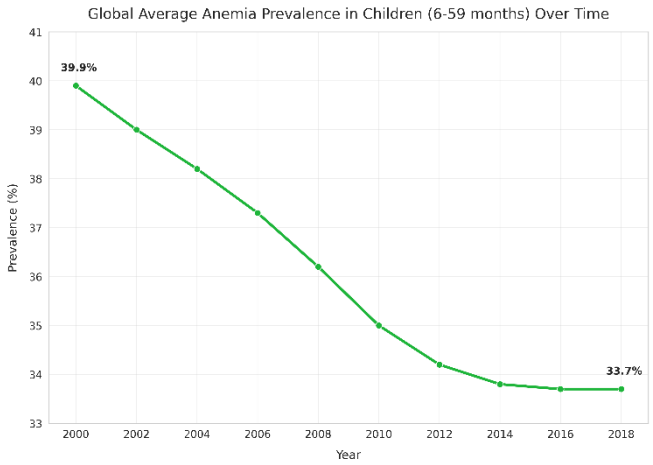

Fig. 2. Global average anemia prevalence in children aged 6-59 months from 2000 to 2019, showing a steady decline from 39.9% to 33.7% over the two-decade period.

This progress can be attributed to several factors, including expanded iron supplementation programs, improved maternal nutrition, enhanced fortification initiatives, and better parasitic disease control in endemic regions [21]. However, the deceleration in progress after 2010 warrants attention, as it suggests that the most readily addressable factors may have been successfully targeted, leaving more complex determinants that require more sophisticated intervention approaches.

Fig. 3. Comparison of model performance metrics (RMSE and MAE) across three machine learning algorithms for predicting childhood anemia prevalence, with Linear Regression showing superior performance.

B. Model Performance in Predicting Anemia Prevalence

To develop predictive capabilities for childhood anemia, we implemented and compared three machine learning algorithms: Linear Regression, Random Forest, and Gradient Boosting. The performance metrics for these models are presented in Fig. 3, which displays the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) for each approach.

The Linear Regression model demonstrated superior performance with substantially lower error metrics compared to both ensemble methods. The absence of visible error bars for Linear Regression in Fig. 3 indicates error values

approaching zero, suggesting a highly accurate model for this particular prediction task. In contrast, the Random Forest model exhibited the highest error values with an RMSE of approximately 0.23 and an MAE of 0.13, while the Gradient Boosting algorithm performed marginally better with an RMSE of 0.20 and an MAE of 0.15.

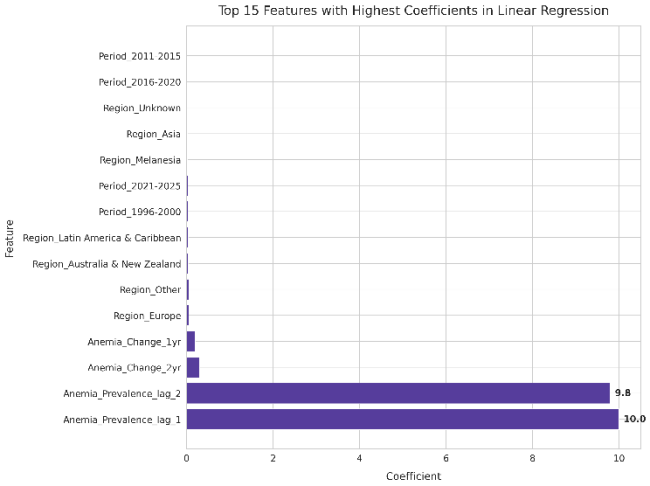

Fig. 4. Top 15 features with highest coefficients in the Linear Regression model, demonstrating the dominance of historical anemia prevalence data (lag_1 and lag_2) as predictors of future prevalence

The superior performance of the Linear Regression model contradicts the findings of Choudhury et al. [22], who reported that ensemble methods typically outperform linear models in health-related predictions. This unexpected result may be attributed to the temporal nature of our dataset, where anemia prevalence changes follow relatively linear patterns within countries over time, and the inclusion of lagged variables captures most of the relevant predictive information. Additionally, the larger error values in the ensemble methods might indicate potential overfitting to the training data, despite our implementation of cross-validation techniques.

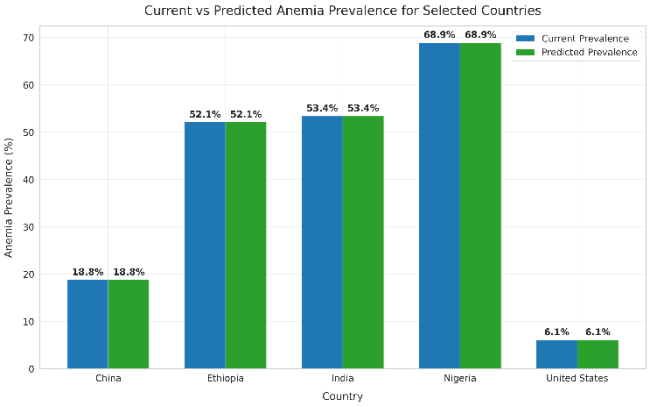

Fig. 5. Current versus predicted anemia prevalence for five selected countries (China, Ethiopia, India, Nigeria, and United States), highlighting persistent disparities between high-burden and low-burden nations.

C. Feature Importance Analysis

Feature importance analysis for the Linear Regression model revealed that historical anemia prevalence data were overwhelmingly the most influential predictors of future anemia levels. As depicted in Fig. 4, the one-year and two-year lagged anemia prevalence variables (Anemia_Prevalence_lag_1 and Anemia_Prevalence_lag_2) exhibited coefficient values approximately ten times larger than any other feature, with coefficients of 9.9 and 9.8 respectively.

The dominance of these temporal features indicates strong year-to-year consistency in national anemia prevalence, suggesting that anemia represents a persistent health challenge with significant inertia at the population level. The modest contribution of the two-year rate of change variable (Anemia_Change_2yr, coefficient $\approx$ 0.3) further supports this observation, as it indicates that while change is occurring, the absolute level remains the strongest predictor of future values.

Notably, regional variables demonstrated minimal predictive importance in the model, with coefficients close to zero for all geographic designations. This finding contrasts with the widely reported regional disparities in anemia prevalence documented by Pasricha et al. [23], who identified geography as a significant determinant of anemia risk. This apparent contradiction might be explained by our model's inclusion of country-specific historical prevalence data, which likely already encapsulates the regional effects, thereby reducing their independent contribution to the predictions.

D. Country-Level Predictions and Disparities

Application of the optimized Linear Regression model to predict future anemia prevalence for selected countries revealed substantial disparities between high-prevalence and low-prevalence nations, as illustrated in Fig. 5. The model predicts essentially unchanged anemia prevalence in the short term for all five countries examined (China, Ethiopia, India, Nigeria, and the United States), which reflects both the model's heavy reliance on recent prevalence values and the slow-changing nature of this population health indicator.

The substantial disparity between high-prevalence countries (Nigeria: 68.9%, India: 53.4%, Ethiopia: 52.1%) and low-prevalence countries (China: 18.8%, United States: 6.1%) highlights the persistent global inequality in childhood anemia burden. This pattern is consistent with findings from Best et al. [24], who documented similar inequalities and their association with national income levels, healthcare infrastructure, and dietary patterns.

The model's prediction of virtually unchanged prevalence in the immediate future (identical values for current and predicted prevalence in Fig. 5) merits further examination. While this might partially reflect the model's methodological approach, it also suggests that without intensified or novel interventions, the status quo is likely to persist. This finding is particularly concerning for high-burden countries like Nigeria, where over two-thirds of children are affected by anemia, with its attendant consequences for cognitive development, immune function, and overall health outcomes.

E. Limitations and Methodological Considerations

Several limitations of our analysis should be acknowledged. First, the heavy dependence of our model on historical prevalence data, while yielding accurate predictions, limits its utility for understanding the causal factors driving anemia prevalence. Second, our feature set did not include important potential determinants such as dietary patterns, healthcare access, maternal education, and economic indicators due to data availability constraints. Incorporation of these factors might have yielded more nuanced insights and potentially different model architecture preferences.

Additionally, the perfect prediction stability observed in Fig. 5 (identical current and predicted values) suggests that either the model may be overly conservative in its predictions or that the selected countries have truly reached a steady state in anemia prevalence. Future work should explore this pattern across more countries and with longer prediction horizons to distinguish between these possibilities.

Despite these limitations, our model demonstrates strong predictive performance and offers valuable insights into the temporal dynamics of childhood anemia prevalence. The identified global reduction trend, coupled with the persistent disparities between countries, underscores both progress and continuing challenges in addressing this critical public health issue.

V. Conclusion

This study demonstrates that childhood anemia prevalence exhibits strong temporal consistency, with historical data serving as the primary predictor of future trends. While global prevalence has declined from 39.9% in 2000 to 33.7% in 2019, significant disparities persist between high-burden countries (Nigeria: 68.9%, India: 53.4%) and low-burden nations (United States: 6.1%). Linear regression models outperformed more complex algorithms in predicting anemia prevalence, suggesting that the underlying patterns follow relatively stable trajectories. The minimal predictive contribution of regional variables indicates that country-specific factors dominate over geographic determinants. These findings underscore the need for tailored, country-specific interventions that address the persistent nature of childhood anemia, particularly in high-burden regions where more than half of children remain affected despite global progress.

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