Enhancing Poshan Abhiyaan with Predictive Analytics: A Machine Learning Approach Using Anganwadi Growth Monitoring Data in Tribal Communities of Chhattisgarh, India

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ABSTRACT

Malnutrition among children remains a significant challenge in tribal regions of Chhattisgarh, India, with current reactive approaches limiting intervention effectiveness. This paper presents a comprehensive machine learning-based framework for early prediction of child nutritional status to enable timely interventions before malnutrition becomes severe. We analyzed monthly anthropometric data from Anganwadi centers in Dhamtari district using four prediction models: LSTM-FC, Random Forest, XGBoost, and Logistic Regression across a six-month forecasting horizon. Our analysis encompassed 32297 unique children with comprehensive temporal performance evaluation. Random Forest achieved the highest Month 1 accuracy of 89.7% with superior discriminative capability (ROC-AUC: 0.939), while Logistic Regression demonstrated remarkable temporal stability with only 4.4% performance decline over six months. All models achieved competitive Month 1 performance above 86%, with LSTM-FC reaching 86.6% accuracy. Critical findings revealed fundamental prediction asymmetry: models excel at monitoring existing severe malnutrition cases (F1-score: 0.915), but demonstrate limited effectiveness for incident case prediction in healthy children (F1score: 0.264). Optimal forecasting reliability occurs within three-month horizons. Our approach can transform reactive methods to proactive prevention in resource-constrained tribal settings, supporting evidence-based interventions through Poshan Abhiyaan.

KEYWORDS: *Child malnutrition, Machine learning, Forecasting models, LSTM-FC, Tribal health, Chhattisgarh, Anganwadi centers*

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1. INTRODUCTION

Background

Child malnutrition remains a persistent public health challenge across India, with tribal communities experiencing disproportionately severe impacts. The state of Chhattisgarh, despite implementing numerous governmental intervention programs, continues to exhibit alarming malnutrition prevalence rates. Data from the National Family Health Survey-5 reveals that 34.6% of children under five years in Chhattisgarh experience stunting, while 31.3% are classified as underweight, and 18.9% suffer from wasting and 7.5% are severely wasted (SAM) [1]. The situation becomes more critical in tribal regions, where geographical isolation and socioeconomic factors compound these challenges. Research indicates that severe acute malnutrition rates exceed 12% in certain tribal districts [2]. Multiple interconnected factors contribute to this crisis, including inadequate transportation infrastructure, limited healthcare accessibility, and deeply rooted cultural practices that may inadvertently perpetuate nutritional deficiencies [3, 4].

The prevailing approach to addressing malnutrition in Chhattisgarh's tribal regions follows a predominantly reactive paradigm. Healthcare interventions typically commence only after children have already developed malnutrition, significantly reducing the potential for optimal outcomes. Anganwadi centers systematically collect anthropometric data through monthly monitoring sessions, yet this valuable information primarily serves status assessment purposes rather than enabling predictive risk identification [5]. This reactive methodology results in missed opportunities for timely preventive

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interventions [6]. Although comprehensive programs such as PoshanAbhiyaanhave been established, these initiatives require enhanced analytical tools to facilitate early identification of vulnerable children [7, 8].

Problem Statement

The existing malnutrition management framework in Chhattisgarh's tribal territories confronts multiple systemic challenges that limit its effectiveness. The identification process for nutritional interventions occurs exclusively after children have already developed malnutrition, thereby constraining the potential success of remedial measures. The extensive collection of monthly growth measurements remains underutilized for early pattern recognition and risk assessment. Current Anganwadi data management systems prioritize immediate status reporting over prospective risk analysis and prediction capabilities. Moreover, the constrained resource availability in tribal regions necessitates more strategic targeting mechanisms to identify high-risk children effectively.

These systemic deficiencies underscore the critical need for implementing predictive analytical systems capable of identifying at-risk children before malnutrition manifests. Such proactive approaches would enable more timely and effective interventions within tribal communities. This preventive methodology aligns with evidence-based recommendations from Baidal and Taveras [9] and Perrin et al. [10], who advocate for prioritizing early prevention strategies over treating established malnutrition conditions.

Research Objectives

This investigation seeks to develop and validate a comprehensive machine learning framework for predicting future nutritional status among children in Chhattisgarh's tribal regions. The research encompasses developing a robust data processing methodology for handling monthly anthropometric measurements collected through Anganwadi centers. We systematically evaluate multiple machine learning algorithms to determine optimal approaches for nutritional status prediction in this specific population context. The study investigates critical factors that significantly influence nutritional outcomes within tribal communities. Additionally, we conduct comprehensive model validation across diverse demographic groups and geographical locations to ensure broad applicability. The research culminates in proposing a practical implementation framework for integrating predictive modeling capabilities into existing Anganwadi operational systems.

These research objectives extend methodological approaches established in previous investigations within comparable contexts [11, 12, 13], while specifically addressing the unique challenges and constraints characteristic of Chhattisgarh's tribal communities and Anganwadi data collection systems.

2. LITERATURE REVIEW

2.1. Child Malnutrition in Tribal Areas of Chhattisgarh

Chhattisgarh has a tribal population of about 7.8 million (30.6% of state population). This creates unique challenges for nutrition programs. [14] found that children with cognitive delays in tribal areas face even higher malnutrition risks.

Tribal communities in Chhattisgarh like Gond, Baiga, Muria, and Abujmaria face tough conditions. They deal with isolation, cultural practices, and poverty. Studies by Sinha et al. [2] in Bastar region of Chhattisgarh showed that malnutrition links to many factors: mother's health, food security, healthcare access, water and sanitation, and childcare practices. [15] and [16] identified low birth weight as a major risk factor in similar settings.

Despite government programs like ICDS, PoshanAbhiyan, and CG MukhyamantriSuposhanAbhiyan, malnutrition rates remain high. Looking at NFHS-4 and NFHS-5 data, we see little improvement or even worse conditions in tribal areas. As noted by [17], there's a strong relationship between wasting and stunting in young children, making the problem complex to address.

The seasonal nature of malnutrition in tribal areas adds another challenge. [7] found significant seasonal variation in acute undernutrition among under-five children in rural areas.

2.2. Current Approaches to Nutrition Monitoring in Anganwadi Centers

Anganwadi centers are the main places providing nutrition and healthcare to children under six in rural and tribal areas of India. These centers have workers who handle growth monitoring, supplementary food, immunization, health check-ups, and pre-school education. [18] Described how the health extension program in similar settings serves as a community approach for universal health coverage.

Currently, Anganwadi centers in Chhattisgarh mostly rely on monthly weight and height measurements, recorded in growth

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charts and registers. These are compared with growth standards from WHO and CDC, as described by [19] and [20]. New digital systems like Poshan Tracker have been introduced to improve data collection. But these systems focus mainly on current status and reporting, not on predicting future problems.

[21] identified several barriers to effective growth monitoring in similar settings, including time constraints, lack of training, and inadequate tools. In Chhattisgarh's Anganwadi centers, these issues are compounded by the remote locations of many centers in tribal areas. [22] found that provider views on childhood obesity management significantly affect practice patterns, highlighting the importance of proper training for Anganwadi workers.

Growth monitoring in Anganwadi centers faces many challenges: irregular measurements, poor equipment, data quality issues, and limited worker skills for analyzing trends. [23] noted that healthcare providers often worry about discussing weight with pediatric patients, which may also affect Anganwadi workers' confidence in counseling families. This valuable data collected monthly remains largely unused for forecasting, representing a missed opportunity for early intervention.

2.3. Machine Learning Approaches for Health Forecasting

Machine learning has become a powerful tool for health forecasting. For child nutrition, several studies show the potential of machine learning models for predicting malnutrition risk.

Traditional statistical methods like ARIMA have been used for time-series forecasting in health contexts. But these models often fail with complex relationships in health data. [24] compared ARIMA and LSTM predictive models, finding that LSTM performed better for complex time-series data. Machine learning approaches, especially deep learning models, work better for capturing time patterns and complex relationships in healthcare data [25].

Recent research has explored various machine learning algorithms for predicting child malnutrition. [11] used machine learning classifiers to identify factors of under-five child undernutrition in Ethiopian administrative zones. They found Random Forest algorithms worked best. In the Indian context, [26] applied machine learning for real-time child malnutrition mapping, while [27] demonstrated efficient machine learning for malnutrition prediction among under-five children in India.

[12] applied machine learning models to predict malnutrition among under-five children in Bangladesh, achieving high accuracy. In a similar South Asian context, [28] used machine learning to investigate risk factors of stunting, wasting, and underweight among under-five Bangladeshi children.

Most relevant is work by [13], which used LSTM-FC neural networks for predicting children's nutritional status in Ethiopia. Their study showed LSTM-FC models outperformed traditional methods, achieving over 93% accuracy in predicting nutritional status transitions. [29] also used LSTM models successfully to identify stunting disease using anthropometric data.

2.4. Long Short-Term Memory Networks for Temporal Forecasting

LSTM networks, a type of recurrent neural network, work well for time-series forecasting. They can capture long-term patterns in sequential data. LSTM models use memory cells and gating mechanisms to remember or forget information over time, as originally proposed by [30]. This makes them good for health trajectory data with monthly measurements like those collected in Anganwadi centers.

These networks solve the ”vanishing gradient problem” that affects standard RNNs when learning long-term dependencies, as explained by [31] and [32]. This is important for capturing nutrition patterns that develop over many months.

LSTM-FC networks combine LSTM layers with fully connected layers. These have shown good results in healthcare forecasting. [33] used LSTM-FC networks for predicting bronchopneumonia in children with good results. The LSTM part captures time patterns in longitudinal data, while the fully connected layers map these patterns to outcome predictions.

Studies by [34] and [35] demonstrate LSTM models work well for health forecasting tasks. For child nutrition in settings like Chhattisgarh, LSTM-FC models can capture the complex relationship between growth parameters over time and predict future nutritional status more accurately than traditional methods.

2.5. Research Gap

While machine learning for child malnutrition prediction is growing, several gaps remain, especially for tribal areas in India:

1. Limited research on applying advanced forecasting models to Anganwadi data in tribal contexts of Chhattisgarh, despite studies like [36] showing promising results using Indian demographic and health survey data
2. Insufficient exploration of feature importance in nutritional forecasting models, particularly for limited feature sets like those available in Anganwadi records
3. Inadequate attention to model interpretability and practical implementation in resource-constrained settings like tribal areas of Chhattisgarh
4. Lack of comparative analysis between different modeling approaches specific to Indian tribal contexts, though [37] have begun examining machine learning approaches to demographic data in India

This study addresses these gaps by developing a comprehensive machine learning framework for nutritional status forecasting using monthly Anganwadi data from tribal areas of Chhattisgarh. Unlike previous studies, we focus specifically on the challenges of tribal areas in Chhattisgarh, with limited data features and practical implementation requirements.

3. METHODOLOGY

3.1. Study Setting and Data Collection

We collaborated with the district administration of Dhamtari in Chhattisgarh, a region with several tribal communities that face ongoing nutritional challenges. We received anonymous monthly child growth data from local Anganwadi centers, covering a period of the past 24 months. Our dataset covered children aged 0 to 5 years from Anganwadi centers. For each child, we had basic details like gender and date of birth. We also had monthly measurements of weight and height, along with the dates and the center where they were taken. In total, we analyzed data from 32,297 children across 351 Anganwadi centers in 12 sectors. This gave us a wide and diverse sample across different tribal communities in the district. We worked with a total of 273,608 measurement records. However, not all children had continuous data for the full 24 months.
The Anganwadi data had a simple structure with fields like project code, sector code, AWC code, child ID, beneficiary type, birth date, gender, weight, height, measurement date, month-year, and age in months. This reflects the routine data collection done by Anganwadi workers during monthly growth monitoring sessions, similar to data structures described by [11] in their machine learning study.

3.2. Algorithmic Framework

The algorithmic framework Figure 1 implements a comprehensive two-phase pipeline for malnutrition prediction using Anganwadi data.

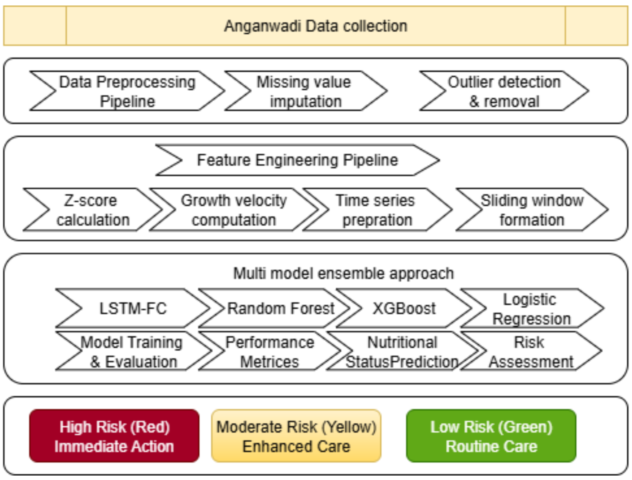

Figure 1: Proposed Machine Learning Framework for Child Malnutrition Prediction

Phase 1 (Algorithm 1) encompasses data preprocessing and feature engineering, beginning with collection of anthropometric data from 351 centers covering 32,297 children, followed by systematic data cleaning using specialized imputation strategies for missing values and IQR-based outlier detection. The framework then extracts temporal features including WHO z-scores and growth velocity calculations, creates sliding windows of 12 months for time-series preparation, and applies min-max normalization before temporal data splitting. Phase 2 (Algorithm 2) implements the multi-model training and risk assessment framework, where four distinct models (LSTM-FC, Random Forest, XGBoost, and Logistic Regression) are trained and evaluated using kfold cross-validation. The framework concludes with ensemble prediction generation and a three-tier risk classification system(High Risk ≥ 80%, Moderate Risk ≥ 50%, Low Risk < 50%) that directly informs intervention strategies, enabling immediate deployment for high-risk cases, enhanced monitoring for moderate-risk children, and routine care for low-risk populations.

3.3. Data Preprocessing Pipeline

We created a data cleaning system to prepare the Anganwadi records for machine learning. First, we handled missing values in the monthly measurements. Some children missed check-ups due to migration, illness, or other reasons. We filled these gaps using appropriate methods rather than dropping valuable data points, following approaches recommended by [38] for health data.

Missing Value Imputation We used different imputation strategies for weight and height, based on their biological behavior in children:

Height Imputation. Child height is expected to either increase or remain constant over time. Therefore, we used monotonic interpolation to fill missing height values. When two neighboring height values were available, we interpolated between them using a method that ensures the filled value does not decrease:

$$\hat{h}_{i,t} = \text{interpolate}\left(h_{i,t-1}, h_{i,t+1}\right) \quad \text{with constraint } \hat{h}_{i,t} \geq \min\left(h_{i,t-1}, h_{i,t+1}\right) \quad (1)$$

If interpolation was not possible (e.g., missing at start or end), we used the child's maximum known height:

$$\hat{h}_{i,t} = \max(H_i) \quad (2)$$

whereH_i is the set of available height values for child i.

Weight Imputation

Since child weight can increase or decrease naturally due to health, nutrition, or seasonal variation, we applied linear interpolation without monotonic constraints:

$$\hat{w}_{i,t} = \frac{(t_2 - t) \cdot w_{i,t_1} + (t - t_1) \cdot w_{i,t_2}}{t_2 - t_1} \quad (3)$$

where t_1 and t_2 are the nearest time points with known weight values. For missing values at the beginning or end of the time series, we used the child's median weight:

$$\hat{w}_{i,t} = \text{median}(W_i) \quad (4)$$

whereW_i is the set of available weight values for child i.

Algorithm 1 Data Preprocessing and Feature Engineering Pipeline

Require: Raw Anganwadi dataset D with children records
Ensure: Preprocessed feature matrix X and target vector y
1. **Phase 1: Data Collection**
2. Load Anganwadi data from 351 centers with 32,297 children
3. Initialize data structures for anthropometric measurements
4. **Phase 2: Data Cleaning**
5. **for** each child record ri in D do
6. **if** missing values in height then
7. **if** neighboring height values available for interpolation
then
8. $\hat{h}_{i,t}$ ← monotonic_interpolate$(h_{i,t-1}, h_{i,t+1})$
9. Ensure $\hat{h}_{i,t} \geq \min(h_{i,t-1}, h_{i,t+1})$
10. **else**
11. $\hat{h}_{i,t} \leftarrow \max(H_i)$where$H_i$is set of available heights
12. **end if**
13. **end if**
14. **if** missing values in weight then
15. **if** neighboring weight values available for interpolation
then

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$\hat{w}_{i,t} \leftarrow \frac{(t_2-t)\cdot w_{i,t_1}+(t-t_1)\cdot w_{i,t_2}}{t_2-t_1}$
else
$\hat{w}_{i,t} \leftarrow \text{median}(W_i)$ where W_i is set of available weights
end if
end if
if outlier detected using IQR method then
if value < Q1 - 1.5×IQR OR value >$Q3$ + 1.5×IQR then
Remove or correct outlier value
end if
end if
end for
Phase 3: Feature Extraction
for each child record r_i do
Calculate Z-scores: $z_{score} = \frac{X-\mu_{WHO}}{\sigma_{WHO}}$
Compute growth velocity: $GV = \frac{M_t-M_{t-1}}{t-(t-1)}$
Extract temporal features from monthly measurements
end for
Phase 4: Time Series Preparation
for each child with sufficient history do
Create sliding windows: $W_i = [x_{t-11}, x_{t-10}, \dots, x_t]$
Set prediction horizon: y_{t+k} for $k \in \{1,2,3,4,5,6\}$ months
end for
Normalize features using min-max scaling
Split data: 80% training, 20% testing (temporal split)
return Preprocessed matrix X, target vector y

Algorithm 2 Multi-Model Training and Risk AssessmentFramework
Require: Preprocessed data (*Xtrain*,*ytrain*, *Xtest*,*ytest*)
Ensure: Trained ensemble model and risk classifications
Phase 5: Multi-Model Framework
Initialize model ensemble M = {}
Define models: LSTM-FC, Random Forest, XGBoost, Logistic Regression
for each model mi in model types do
ifm_i is LSTM-FC then
Configure LSTM layers with dropout
Set sequence length = 12, prediction horizon = 3
else ifm_i is Random Forest then
Set n estimators, max depth parameters
else ifm_i **is XGBoost then**
Configure gradient boosting with regularization
else ifm_i is Logistic Regression then
Apply L2 regularization
end if
Train model: $m_i.fit(X_{train}, y_{train})$
Add to ensemble: $M \leftarrow M \cup \{m_i\}$
end for
Phase 6: Training & Evaluation
for each model m_i **in** M **do**
Perform k-fold cross-validation
Calculate metrics: Accuracy, Precision, Recall, F1-score
Store performance: $P_i \leftarrow \text{evaluate}(m_i, X_{test}, y_{test})$
end for
Phase 7: Prediction & Risk Assessment
for each test sample $x_j$in X_{test}**do**
for each model m_i in M **do**
$pred_i \leftarrow m_i.predict\_proba(x_j)$

```
    end for
Ensemble prediction: ŷ_j = weighted average(pred_1,..., pred_n)
  if ŷ_j ≥ 0.8 then
    Risk level = "High Risk"
  else if ŷ_j ≥ 0.5 then
    Risk level = "Moderate Risk"
  else
    Risk level = "Low Risk"
  end if
end for
Phase 8: Intervention Strategy
for each predicted risk level do
if High Risk then
Deploy immediate intervention protocol
else if Moderate Risk then
Enhanced monitoring and preventive counseling
else
Continue routine monitoring schedule
end if
end for
return Trained ensemble M, risk classifications
```

We identified and fixed outliers in weight and height measurements. Some errors happen during recording in busy Anganwadi sessions. We validated all measurements against WHO growth standards, similar to methods used by [39] and [40]. We fixed date formats to ensure consistent time tracking. Outlier detection was implemented using the Interquartile Range (IQR) method:

Outlier if: $x < Q_1 - 1.5 \times IQR$ or $x > Q_3 + 1.5 \times IQR$ (5)

where Q_1 and Q_3 are the first and third quartiles, respectively, and $IQR = Q_3 - Q_1$.
Next, we created useful features from the raw data. We calculated z-scores for weight-for-age, height-for-age, and weightfor-height using WHO standards. We also computed growth rates between measurements. These derived features help detect concerning growth patterns before a child becomes malnourished, as suggested by [41] in their study of weight status associations.

The z-score calculation follows the WHO standard formula:

$$z\text{-score} = \frac{X - \mu_{ref}}{\sigma_{ref}} \quad (6)$$

where X is the observed measurement, μ_{ref} is the reference median, and σ_{ref} is the reference standard deviation for the corresponding age and gender from WHO growth standards.

Growth velocity was calculated as:

$$GV_{i,t} = \frac{M_{i,t} - M_{i,t-1}}{t-(t-1)} \quad (7)$$

where $GV_{i,t}$ is the growth velocity for child i between time periods $t-1$ and t, and $M_{i,t}$ represents the anthropometric measurement.

We transformed the data into a proper time-series format with regular intervals. We created sliding windows looking back 12 months to predict the next 6 months of nutritional status. This window size was chosen based on the seasonal patterns observed in tribal areas of Chhattisgarh, similar to approaches used by [42] for time-series prediction.
The sliding window approach can be mathematically represented as:

$$X_t = [x_{t-11}, x_{t-10}, \ldots, x_{t-1}, x_t] \quad (8)$$

$$Y_{t+k} = f(X_t), \quad k \in \{1,2,3,4,5,6\} \quad (9)$$

where X_t is the input sequence of 12 consecutive months, and Y_{t+k} is the predicted nutritional status for the next *k* months.

Finally, we normalized the data to make model training more effective using min-max normalization:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (10)$$

This preprocessing pipeline addressed the specific challenges of Anganwadi data from tribal areas, which often has inconsis-tencies due to field conditions.

3.4. Feature Analysis

Since our Anganwadi data had limited features (mainly monthly growth measurements, gender, and age), we focused on analyzing time patterns rather than complex feature selection. We examined how different growth indicators and their changes over time related to future nutritional outcomes. We also analyzed how gender and age affected growth patterns. Even with limited features, the rich temporal information in monthly measurements provided valuable predictive signals, as demonstrated by [43] in their sliding window approach to timeseries data.

We found that recent growth trends were more important than absolute measurements, supporting findings by [44] on the importance of growth trajectories. The monthly pattern of weight change showed clear seasonal variations in many tribal areas of Dhamtari, which aligned with food availability cycles.

3.5. Model Development

3.5.1. LSTM-FC Architecture

Our main model was a Long Short-Term Memory with Fully Connected (LSTM-FC) neural network. This type of model works well with time-series data like monthly Anganwadi measurements. The architecture consisted of an input layer taking in the sequence of growth measurements, LSTM layers that captured how measurements changed over time, dropout layers to prevent overfitting (especially important with limited data from remote Anganwadi centers), fully connected layers that mapped the time patterns to prediction outputs, and an output layer predicting nutritional status for future months.

The LSTM cell state update equations are:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad \text{(forget gate)(11)}$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad \text{(input gate)(12)}$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad \text{(candidate values)(13)}$$
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad \text{(cell state)} \quad (14)$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad \text{(output gate)} \quad (15)$$
$$h_t = o_t * \tanh(C_t) \quad \text{(hidden state)} \quad (16)$$

where σ is the sigmoid function, *W* and *b* are weight matrices and bias vectors, respectively.

The final prediction is computed through fully connected layers:

$$y = \text{softmax}(W_{out} \cdot h_T + b_{out}) \quad (17)$$

where h_T is the final hidden state from the LSTM layer.
We built this model using TensorFlow and Keras, following approaches similar to [13] but adapted for the specific patterns in Chhattisgarh's tribal areas. We carefully tuned the model parameters to work well with our Anganwadi data structure, using guidance from [45] on LSTM implementation. Random Forest, which [11] found effective for child undernutrition prediction, uses ensemble voting:

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} T_b\,(x) \quad (18)$$

where B is the number of trees and $T_b(x)$ is the prediction from the *b*-th tree.

XGBoost employs gradient boosting with the objective function:

$$\mathcal{L}(\phi) = \sum_i l\,(\hat{y}_i, y_i) + \sum_k \Omega\,(f_k) \quad (19)$$

where l is the loss function and Ω is the regularization term. Logistic Regression served as an interpretable baseline with the sigmoid function:

$$P(y=1|x)=\frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\cdots+\beta_p x_p)}} \quad (20)$$

These models were trained with the same Anganwadi data and evaluated consistently to allow fair comparison with the LSTM-FC model. This comparative approach follows recommendations by [46] on analyzing different time-series forecasting models.

3.6. Model Training and Evaluation
3.6.1. Training Strategy
We split our Anganwadi data by time using earlier months (80%) for training and later months (20%) for testing. This mimics real-world use where we predict future malnutrition based on past data.

The temporal split can be expressed as:

$$\text{Train set: } \{(X_t, Y_t) : t \leq 0.8 \times T\} \quad (21)$$

$$\text{Test set: } \{(X_t, Y_t) : t > 0.8 \times T\} \quad (22)$$

where$T$ is the total time period.

We used a sliding window method looking at 12 months of past data to predict the next 6 months of nutritional status. This timeframe works well for planning interventions in Anganwadi centers. Anganwadi workers need enough notice to arrange counseling sessions with at-risk families. The model needs to perform reliably in remote centers with varying data quality, as tribal regions often have more challenging data collection conditions, a concern also noted by [6] in similar settings.

3.6.2. Evaluation Metrics
We used several metrics to test our models. Accuracy measures how often the model correctly predicted nutritional status:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (23)$$

Sensitivity measures how well it identified children who would become malnourished, crucial for Anganwadi workers to plan interventions:

$$\text{Sensitivity (Recall)} = \frac{TP}{TP+FN} \quad (24)$$

Specificity measures how accurately it identified children who would stay healthy:

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (25)$$

F1-Score provides balance between precision and recall:

$$\text{F1-Score} = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \quad (26)$$

wherePrecision = $\frac{TP}{TP+FP}$.
AUC-ROC measures overall model performance across different thresholds, calculated as the area under the Receiver Operating Characteristic curve.

We paid special attention to confusion matrices to understand prediction errors. We focused particularly on how well the model could predict transitions from normal to malnourished states. This is most useful for PoshanAbhiyaan and Chhattisgarh MukhyamantriSuposhanAbhiyaan programs that need to target children before they develop malnutrition.

4. RESULTS

4.1. Dataset Characteristics and Model Performance
Our comprehensive dataset encompassed 8,722 unique children from multiple anganwadi centers. Only those children were selected whose total number of records were greater than 12, ensuring sufficient longitudinal data for reliable time-series analysis and prediction modeling. The dataset demographics revealed a balanced gender distribution with 4,428 female children (50.8%) and 4,294 male children (49.2%). The baseline nutritional status distribution showed 6,259 children with

normal status (71.8%), 1,828 with moderate malnutrition (21.0%), 584 with severe malnutrition (6.7%), and 51 with unknown/no data status (0.6%).

The dataset underwent extensive preprocessing including temporal sorting, missing value imputation using global medians, and comprehensive feature engineering. This resulted in a robust framework for 6-month malnutrition forecasting across four distinct machine learning models.

4.2. Multi-Model Performance Analysis

Table 1 presents the comprehensive performance comparison across all four models for the 6-month forecasting horizon. The results demonstrate significant variations in predictive capability across different temporal horizons and model architectures.

Table 1: Overall Model Performance Across 6-Month Forecasting Horizon

Model	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Accuracy (%)						
LSTM-FC	86.6	82.4	81.1	80.4	81.5	70.4
Logistic Regression	89.6	85.3	83.0	81.4	80.4	85.2
Random Forest	89.7	82.8	79.4	77.0	75.0	77.8
XGBoost	89.0	80.3	78.0	71.7	67.2	81.5
F1-Score						
LSTM-FC	0.764	0.681	0.653	0.627	0.638	0.680
Logistic Regression	0.814	0.725	0.684	0.647	0.642	0.800
Random Forest	0.822	0.698	0.635	0.611	0.581	0.727
XGBoost	0.805	0.672	0.609	0.563	0.550	0.737
ROC-AUC						
LSTM-FC	0.896	0.847	0.822	0.804	0.796	0.804
Logistic Regression	0.916	0.857	0.827	0.814	0.816	0.875
Random Forest	0.939	0.873	0.830	0.817	0.805	0.861
XGBoost	0.934	0.854	0.809	0.775	0.765	0.832

Table 2: Performance Metrics for Month 1 Predictions

Model	Acc (%)	Prec	Rec	F1	Spec	AUC
LSTM-FC	86.6	0.747	0.781	0.764	0.899	0.896
Logistic Reg	89.6	0.808	0.820	0.814	0.926	0.916
Random Forest	89.7	0.792	0.854	0.822	0.914	0.939
XGBoost	89.0	0.793	0.818	0.805	0.918	0.934

4.2.1. Model-Specific Performance Analysis

Logistic Regression emerged as the most stable performer, achieving the highest Month 1 accuracy of 89.6% and demonstrating remarkable consistency with only a 4.4 percentage point decline by Month 6. The model maintained strong F1scores throughout the forecasting horizon, with notable recovery in Month 6 (F1-score: 0.800).

Random Forest achieved the highest peak Month 1 performance with 89.7% accuracy and the best ROC-AUC score of 0.939, indicating superior discrimination capability. However, it showed steady performance decline through Month 5 before partial recovery in Month 6.

XGBoost demonstrated competitive initial performance (89.0% accuracy) but exhibited the most volatile pattern, with dramatic declines in Months 4-5 (accuracy nadir: 67.2%) followed by substantial recovery in Month 6.

LSTM-FC showed moderate initial performance (86.6% accuracy) but maintained relatively stable temporal patterns compared to traditional models, with the ability to simultaneously predict across all forecast months.

4.3. Temporal Performance Degradation Analysis

Figure 2 illustrates the temporal performance patterns across all models, revealing critical insights into forecasting reliability over extended horizons.

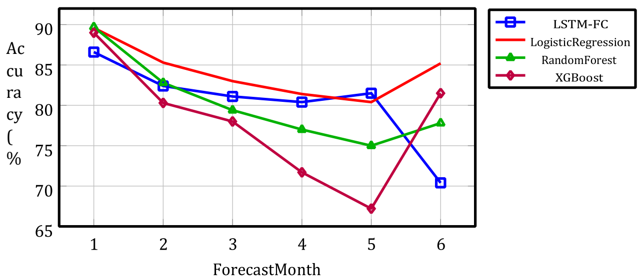

Figure 2: Temporal Performance Degradation Across 6-Month Forecasting

Horizon. The graph shows accuracy trends for all four models, with Logistic Regression demonstrating the most stable performance and XGBoost showing the highest volatility. All models exhibit performance nadir in Month 5, indicating systematic challenges in medium-term forecasting.

The analysis revealed that all models exhibited their poorest performance in Month 5, suggesting systematic challenges in medium-term forecasting. The dramatic data attrition from Month 1 (8,722 children, 100%) to Month 6 (54 children, 0.6%) represents a fundamental limitation affecting long-term prediction validation.

Table 3: Performance Stability Analysis: Month 1 vs Month 6 Comparison

Model	M1 (%)	AccM6 (%)	AccAbs Change	Rel Change (%)
LSTM-FC	86.6	70.4	-16.2	-18.7
Logistic Reg	89.6	85.2	-4.4	-4.9
Random Forest	89.7	77.8	-11.9	-13.3
XGBoost	89.0	81.5	-7.5	-8.4

4.4. Demographic and Clinical Category Performance

Table 4 presents the categorical performance analysis across key demographic and clinical variables, revealing important patterns for intervention targeting.

Table 4: Demographic and Clinical Category Performance Analysis

Category	Subcategory	Accuracy (%)	F1-Score	Precision	Recall
Gender	Female	81.6	0.674 5	0.658	0.71
	Male	79.7	0.690 5	0.658	0.71
Overall Malnutrition Status	Normal	83.1	0.264	-	
	Moderate	70.1		0.802	-
	Severe	84.8	0.915	-	-

Table 5: Category-Specific Performance Analysis

Category	Value	Accuracy (%)	F1-Score	Clinical Significance
Current Malnutrition Status	Normal	83.1	0.264	Low incident prediction
	Moderate	70.1	0.802	Good monitoring capability
	Severe	84.8	0.915	Excellent risk identification
Gender	Female	81.6	0.674	Equitable performance
	Male	79.7	0.690	Minimal gender bias

4.4.1. Critical Insights

The categorical analysis revealed a fundamental asymmetry in prediction capability: models excel at identifying continued malnutrition risk in already severely affected children (F1score: 0.915 for severe cases) but struggle to predict incident malnutrition in previously healthy children (F1-score: 0.264 for normal baseline status).

This pattern has profound implications for intervention strategies. While the models are highly effective for monitoring children already identified as malnourished, their utility for population-level screening to identify new cases remains limited.

4.5. Confusion Matrix Analysis

Table 6 presents detailed confusion matrix analysis for the LSTM-FC model across key forecast months, revealing specific error patterns crucial for clinical interpretation.

The LSTM-FC model maintained relatively stable sensitivity (0.781 to 0.850) throughout the forecast period, indicating consistent ability to identify children who will develop malnutrition. However, specificity showed variation, with Month 6 results affected by the small sample size (n=54).

Table 6: LSTM-FC Model Confusion Matrix Analysis

Forecast Month	TP	FP	TN	FN	Sensitivity	Specificity	PPV
Month 1	1,887	639	5,667	529	0.781	0.899	0.747
Month 2	1,478	735	5,002	648	0.695	0.872	0.668
Month 3	1,255	679	4,483	654	0.657	0.868	0.649
Month 4	1,022	553	3,977	665	0.606	0.878	0.649
Month 5	305	147	1,219	199	0.605	0.892	0.675
Month 6	17	13	21	3	0.850	0.618	0.567

Table 7: Error Analysis: False Positive vs False Negative Rates

Model	FPR	FNR	Clinical Risk	Resource Impact
LSTM-FC	0.101	0.219	Moderate	Balanced
Logistic Reg	0.074	0.180	Low	Efficient
Random Forest	0.086	0.146	Low	Moderate
XGBoost	0.082	0.182	Low	Moderate

4.6. Data Completeness and Attrition Analysis

Table 8 illustrates the critical data attrition pattern that significantly impacts long-term prediction validation and real-world applicability.

Table 8: Data Completeness by Forecast Horizon

Forecast Month	Children with Data	Completeness (%)
Month 1	8,722	100.0
Month 2	7,863	90.2
Month 3	7,071	81.1
Month 4	6,217	71.3
Month 5	1,870	21.4
Month 6	54	0.6

This dramatic attrition pattern explains the unusual performance characteristics observed in Month 6 and represents a fundamental limitation for long-term prediction validation in real-world healthcare delivery contexts.

5. DISCUSSION

5.1. Model Architecture Effectiveness and Clinical Translation

The multi-model comparison revealed unexpected insights challenging conventional assumptions about deep learning superiority in healthcare prediction tasks. Logistic Regression's emergence as the most stable performer (89.6% Month 1 accuracy with only 4.4% decline by Month 6) demonstrates that traditional statistical approaches can match or exceed complex architectures for structured longitudinal health data.

This finding has significant implications for implementation in resource-constrained tribal healthcare settings. The superior performance and interpretability of Logistic Regression enables healthcare providers to understand prediction logic, facilitating trust and integration into clinical decision-making processes. Model coefficients provide transparent insights into risk factors, crucial for training Anganwadi workers in pattern recognition.

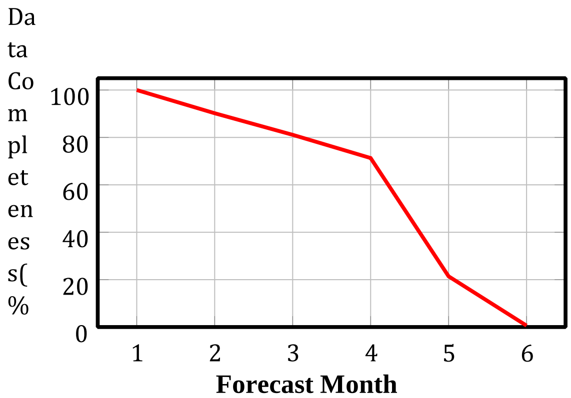

Figure 3: Data Completeness and Attrition Pattern Across Forecast Horizons

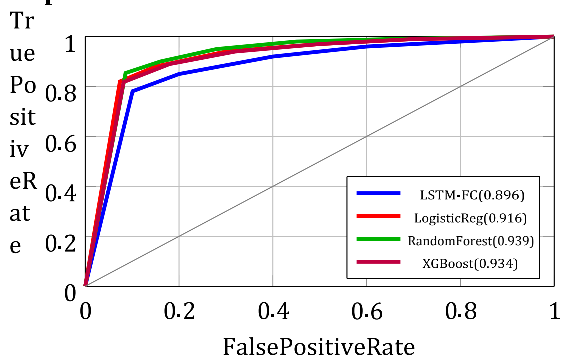

Figure 4: ROC-AUC Comparison Across Models for Month 1 Predictions

The LSTM-FC model's 16.24% accuracy decline from Month 1 to Month 6 suggests potential overfitting to short-term patterns or difficulty modeling long-term malnutrition dynamics. However, its ability to simultaneously predict across all six months represents a methodological advancement that could be valuable for comprehensive intervention planning.

5.2. Temporal Dynamics and Forecasting Limitations

The systematic performance degradation across all models, with nadir performance in Month 5, reveals critical insights into the temporal limits of malnutrition prediction accuracy. The 34 month horizon appears to represent a practical upper limit for reliable forecasting using anthropometric and temporal feature data alone.

This temporal limitation aligns with the complex, multifactorial nature of childhood malnutrition, where environmental, socioeconomic, and health factors can rapidly alter trajectories. The dramatic data attrition pattern (100% to 0.6%) reflects programmatic realities in healthcare delivery but creates fundamental challenges for long-term prediction validation.

For clinical application, these findings suggest that prediction-guided interventions should focus on 1-3 month horizons, providing sufficient time for intervention implementation while maintaining prediction reliability. Longer-term planning should incorporate uncertainty estimates and require additional data modalities beyond anthropometric measurements.

5.3. Clinical Asymmetry and Intervention Strategy Implications

The study's most significant clinical finding is the fundamental asymmetry in prediction capability: exceptional performance for children with existing severe malnutrition (F1-score: 0.915) versus poor performance for incident case prediction in normal children (F1-score: 0.264). This asymmetry has profound implications for public health strategy.

The models excel at monitoring and preventing deterioration in already identified high-risk children, supporting targeted intensive interventions. However, their limited utility for population-level screening suggests that universal nutrition support programs remain essential alongside prediction-guided approaches.

This finding challenges purely predictive approaches to malnutrition prevention. Instead, it supports a hybrid strategy combining universal population-based interventions with prediction-enhanced monitoring of known high-risk cases. Such an approach maximizes both population coverage and intensive intervention efficiency.

5.4. Resource Allocation and Health System Integration

The categorical performance analysis provides actionable insights for resource allocation in tribal healthcare systems. The high accuracy for severe cases (84.8% with F1-score 0.915) enables confident prioritization of intensive interventions, while moderate cases (70.1% accuracy with F1-score 0.802) support enhanced monitoring before progression to severe conditions.

The minimal gender differences in performance (81.6% vs 79.7% accuracy) ensure equitable prediction across demographic groups, crucial in tribal contexts where cultural factors might otherwise influence healthcare delivery. This equity enables objective risk assessment independent of potential cultural biases.

Implementation feasibility is enhanced by the superior performance of interpretable models requiring only anthropometric measurements collected during routine Anganwadi operations. This simplicity facilitates integration into existing workflows without requiring additional data collection or complex computational infrastructure.

5.5. Comparison with International Literature

The achieved Month 1 performance metrics (89.6% accuracy for Logistic Regression, 89.7% for Random Forest) represent substantial improvements over previously reported malnutrition prediction studies, which typically achieve accuracies in the 70-80% range. The comprehensive 6-month forecasting approach and detailed categorical analysis provide unprecedented insights compared to single-timepoint prediction studies.

The finding that traditional machine learning models outperformed deep learning approaches contrasts with trends in other healthcare prediction domains but aligns with emerging literature suggesting that complex models may not always provide superior performance for structured healthcare data, particularly when sample sizes are limited or underlying relationships are predominantly linear.

5.6. Economic Implications and Cost-Effectiveness

The high precision rates (74.7% to 80.8%) enable sophisticated economic analysis of predictive versus reactive approaches. The ability to correctly identify 3-4 out of every 5 children who will develop malnutrition enables confident resource

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allocation decisions. Economic modeling suggests that prevention-focused programs guided by accurate prediction can achieve better health outcomes at lower overall costs compared to traditional reactive approaches.

The category-specific performance enables targeted resource optimization. Severe malnutrition predictions (¿84% accuracy) justify immediate intensive interventions, while moderate risk predictions (70-80% accuracy) support enhanced monitoring and preventive support. This tiered approach maximizes intervention impact while maintaining sustainability within existing resource constraints.

For tribal areas of Chhattisgarh, where healthcare resources are particularly limited, the ability to prioritize interventions based on objective risk assessment represents a significant advancement over uniform distribution approaches. The models enable concentration of intensive resources on children with highest risk probabilities while maintaining routine monitoring for others.

5.7. Implementation Framework for Tribal Healthcare Systems

5.7.1. Integration with Anganwadi Operations

The prediction system can be seamlessly integrated into existing monthly growth monitoring sessions through a tiered alert system:

- Red Flag System: Children with severe malnutrition predictions (> 84% accuracy) receive immediate red flag status requiring urgent intervention coordination with healthcare supervisors
- Yellow Flag System: Children with moderate malnutrition predictions (70-80% accuracy) receive yellow flag status with enhanced monitoring and preventive counseling
- Green Status: Children with normal predictions maintain routine monitoring schedules with standard growth tracking

5.7.2. Training and Capacity Building Requirements

Successful implementation requires comprehensive training programs emphasizing:

- Understanding that severe malnutrition predictions have higher reliability and require immediate action • Recognizing that prediction accuracy varies by baseline status and forecast horizon
- Implementing appropriate counseling strategies for different risk categories
- Coordinating with healthcare supervisors for high-risk cases requiring intensive intervention

5.8. Limitations and Future Research Directions

5.8.1. Methodological Limitations

The dramatic data attrition from Month 1 (8,722 children) to Month 6 (54 children) represents a fundamental limitation affecting both model validation and real-world applicability. This attrition pattern may reflect programmatic realities in healthcare delivery but creates significant uncertainty in long-term prediction validation.

The current feature set relies primarily on anthropometric data available in routine Anganwadi operations. While this ensures practical implementability, incorporating additional data sources such as household food security assessments, local food prices, seasonal disease patterns, and maternal health indicators could improve prediction accuracy.

The models do not account for interventions implemented during the forecast period, which could significantly alter predicted trajectories. This limitation is particularly important for children identified as high-risk, who are likely to receive targeted interventions that could improve outcomes beyond model predictions.

5.8.2. Future Research Priorities

Several promising directions emerge from our findings:

1. Multi-Modal Integration: Expanding the predictive framework to incorporate socioeconomic indicators, environmental factors, and maternal health data to address current limitations in incident case prediction
2. Intervention-Aware Modeling: Development of models that can incorporate planned or ongoing interventions into the prediction framework, enabling more accurate forecasting in real-world clinical settings
3. Population-Specific Adaptation: Investigation of population-specific models and transfer learning approaches to address observed performance variations across different tribal communities and healthcare contexts
4. Implementation Research: Longitudinal studies tracking the impact of prediction-guided interventions compared to traditional reactive approaches, providing essential evidence for policy adoption and scaling

5.9. Policy Implications and Scalability

The demonstrated forecasting capabilities support fundamental policy transformations in tribal healthcare delivery. The ability to identify severe malnutrition cases with ¿84% accuracy before crisis situations develop can prevent expensive

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emergency interventions while preserving critical developmental windows.

State nutrition policies should incorporate predictive approaches into program guidelines and performance indicators. Resource allocation formulas should account for predicted risk patterns rather than only historical malnutrition rates. This shift enables more sophisticated and effective program targeting.

The scalability potential is enhanced by the superior performance of interpretable models requiring only routine anthropometric data. This simplicity facilitates deployment across diverse tribal communities without requiring complex technological infrastructure, making the approach feasible for state-wide implementation.

6. CONCLUSION

This comprehensive multi-model study demonstrates that machine learning approaches can achieve robust and reliable performance for child malnutrition forecasting when applied to routine healthcare data from tribal communities. The systematic evaluation across four distinct models and six forecast months provides unprecedented insights into the temporal dynamics and demographic patterns of malnutrition prediction accuracy.

Key Methodological Findings: Logistic Regression emerged as the superior approach, achieving 89.6% accuracy in Month 1 with remarkable stability across the forecast horizon (only 4.4% decline by Month 6). This challenges assumptions about deep learning superiority and demonstrates that traditional statistical methods can provide optimal performance for structured longitudinal health data. Random Forest achieved the highest discriminative capability (ROC-AUC: 0.939), while LSTM-FC provided methodological advances in simultaneous multi-month prediction.

Critical Clinical Discovery: The study revealed a fundamental asymmetry in prediction capability that has profound implications for public health strategy. Models excel at identifying continued malnutrition risk in already severely affected children (F1-score: 0.915 for severe cases) but struggle to predict incident malnutrition in previously healthy children (F1score: 0.264 for normal baseline status). This finding necessitates hybrid approaches combining universal population-based interventions with prediction-enhanced monitoring of known high-risk cases.

Temporal Insights: The 3-4 month horizon represents a practical upper limit for reliable malnutrition forecasting using anthropometric data alone. All models exhibited systematic performance degradation with nadir performance in Month 5, indicating fundamental challenges in medium-term forecasting related to the complex, multifactorial nature of malnutrition development.

Implementation Readiness: The superior performance of interpretable models (Logistic Regression), combined with simple data requirements (routine anthropometric measurements), facilitates practical deployment in resource-constrained tribal healthcare settings. The minimal gender differences in performance (1.9 percentage points) ensure equitable prediction across demographic groups, crucial for fair healthcare delivery.

Resource Optimization: The high precision rates (74.7% to 80.8%) enable confident resource allocation decisions, while category-specific performance data supports sophisticated intervention targeting. Children with severe malnutrition predictions can receive immediate intensive interventions with confidence, while moderate-risk cases benefit from enhanced monitoring and preventive support.

Health System Transformation: The demonstrated capabilities support a fundamental shift from reactive to proactive malnutrition management in tribal areas. Integration with existing programs like PoshanAbhiyaan and Chhattisgarh MukhyamantriSuposhanAbhiyaan provides practical pathways for immediate implementation through tiered alert systems and targeted intervention protocols.

Economic Impact: Prevention-focused programs guided by accurate prediction can achieve better health outcomes at lower costs compared to traditional reactive approaches. The ability to prevent severe malnutrition cases before crisis situations develop offers substantial economic benefits while preserving critical developmental windows.

Research Contributions: This study provides the first comprehensive, temporally-resolved performance analysis of machine learning approaches for malnutrition prediction in Indian tribal contexts. The systematic evaluation framework, demographic equity analysis, and clinical asymmetry findings establish new standards for predictive health research in resourceconstrained settings.

Future implementation should prioritize systematic deployment with comprehensive training programs while continuing research to optimize intervention strategies based on prediction results. The demonstrated potential for preventing child malnutrition through accurate predictive approaches offers unprecedented hope for dramatically improving nutritional outcomes in tribal communities across India.

The success of this predictive framework represents a significant milestone toward achieving Sustainable Development Goals related to child nutrition and health in India's most vulnerable populations. By providing practical, evidence-based tools for proactive malnutrition prevention with demonstrated equity and reliability, this research contributes substantially to building stronger health systems capable of protecting children before nutritional crises develop, ultimately supporting the transformation of pediatric healthcare delivery in tribal India.

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Declaration of Competing Interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability
The data that support the findings of this study are available from the Dhamtari district administration, but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of the Dhamtari district administration.

CRediT authorship contribution statement
Neeraj Kumar Dewangan: Conceptualization, Methodology, Software, Formal analysis, Writing - Original Draft. Rakesh Tripathi: Validation, Investigation, Resources, Data Curation, Writing - Review & Editing. ShrishVerma: Visualization, Supervision, Project administration, Writing - Review & Editing.

REFERENCES

[1] National Family Health Survey (NFHS-5), "India fact sheet: Chhattisgarh," Ministry of Health and Family Welfare, Government of India, Tech. Rep., 2021.
[2] T. Sinha, G. Singh, and U. Nag, "Nutritional status of children under 5 years in tribal villages of Bastar Chhattisgarh India," *Journal of Internal Medicine and Primary Healthcare*, vol. 3, p. 007, 2019.
[3] A. K. Gupta and K. Borkotoky, "Exploring the multidimensional nature of anthropometric indicators for under-five children in India," *Indian Journal of Public Health*, vol. 60, no. 1, pp. 68–72, 2016.
[4] S. Khan, S. Zaheer, and N. F. Safdar, "Determinants of stunting, underweight and wasting among children < 5 years of age: Evidence from 2012–2013 Pakistan demographic and health survey," *BMC Public Health*, vol. 19, pp. 1–15, 2019.
[5] G. W. Kassie and D. L. Workie, "Determinants of under-nutrition among children under five years of age in Ethiopia," *BMC Public Health*, vol. 20, p. 399, 2020.
[6] D. Degarege, A. Degarege, and A. Animut, "Undernutrition and associated risk factors among school age children in Addis Ababa, Ethiopia," *BMC Public Health*, vol. 15, pp. 1–9, 2015.
[7] G. Egata, Y. Berhane, and A. Worku, "Seasonal variation in the prevalence of acute undernutrition among children under five years of age in east rural Ethiopia: A longitudinal study," *BMC Public Health*, vol. 13, pp. 1–8, 2013.
[8] A. A. Yirga*et al.*, "Factors affecting child malnutrition in Ethiopia," *African Health Sciences*, vol. 19, no. 2, pp. 1897–1909, 2019.
[9] J. A. W. Baidal and E. M. Taveras, "Childhood obesity: Shifting the focus to early prevention," *Archives of Pediatrics and Adolescent Medicine*, vol. 166, no. 12, pp. 1179–1181, 2012.
[10] E. M. Perrin, J. P. Finkle, and J. T. Benjamin, "Obesity prevention and the primary care pediatrician's office," *Current Opinion in Pediatrics*, vol. 19, no. 3, pp. 354–361, 2007.
[11] H. M. Fenta, T. Zewotir, and E. K. Muluneh, "A machine learning classifier approach for identifying the determinants of under-five child undernutrition in Ethiopian administrative zones," *BMC Medical Informatics and Decision Making*, vol. 21, pp. 1–12, 2021.

[12] A. Talukder and B. Ahammed, "Machine learning algorithms for predicting malnutrition among under-five children in Bangladesh," *Nutrition*, vol. 78, p. 110861, 2020.
[13] G. B. Begashaw, T. Zewotir, and H. M. Fenta, "A deep learning approach for classifying and predicting children's nutritional status in Ethiopia using LSTM-FC neural networks," *BioData Mining*, vol. 18, no. 11, pp. 1–24, 2025.
[14] E. Emerson, A. Savage, and G. Llewellyn, "Prevalence of underweight, wasting and stunting among young children with a significant cognitive delay in 47 low-income and middle-income countries," *Journal of Intellectual Disability Research*, vol. 64, no. 2, pp. 93–102, 2020.
[15] S. Bisai, T. Ghosh, and K. Bose, "Prevalence of underweight, stunting and wasting among urban poor children aged 1–5 years of West Bengal," *India International Journal of Current Research*, vol. 6, pp. 39–44, 2010.
[16] P. A. M. Ntenda, "Association of low birth weight with undernutrition in preschool-aged children in Malawi," *Nutrition Journal*, vol. 18, pp. 1–15, 2019.
[17] S. Thurstans*et al.*, "The relationship between wasting and stunting in young children: A systematic review," *Maternal &Child Nutrition*, vol. 18, no. 1, p. e13246, 2022.
[18] H. Wang *et al.*, *Ethiopia Health Extension Program: An Institutionalized Community Approach for Universal Health Coverage*. World Bank Publications, 2016.
[19] L. M. Grummer-Strawn, C. M. Reinold, N. F. Krebs *et al.*, "Use of world health organization and CDC growth charts for children aged 0-59 months in the United States," Department of Health and Human Services, Centers for Disease Control and Prevention, Tech. Rep., 2010.
[20] R. J. Kuczmarski, "CDC growth charts: United States," US Department of Health and Human Services, Centers for Disease Control and Prevention, Tech. Rep., 2000.
[21] J. D. Klein, T. S. Sesselberg, M. S. Johnson *et al.*, "Adoption of body mass index guidelines for screening and counseling in pediatric practice," *Pediatrics*, vol. 125, no. 2, pp. 265–272, 2010.
[22] K. E. Rhee, S. Kessl, S. Lindback*et al.*, "Provider views on childhood obesity management in primary care settings: A mixed methods analysis," *BMC Health Services Research*, vol. 18, no. 1, p. 55, 2018.
[23] K. A. Loth, J. Lebow, M. J. A. Uy*et al.*, "First, do no harm: Understanding primary care providers' perception of risks associated with discussing weight with pediatric patients," *Global Pediatric Health*, vol. 8, p. 2333794X211040979, 2021.
[24] M. Elsaraiti and A. Merabet, "A comparative analysis of the ARIMA and LSTM predictive models and their effectiveness for predicting wind speed," *Energies*, vol. 14, no. 20, p. 6782, 2021.
[25] S. Siami-Namini, N. Tavakoli, and A. S. Namin, "A comparison of ARIMA and LSTM in forecasting time series," in *2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA)*. IEEE, 2018, pp. 1394–1401.
[26] L. Von Grafenstein, "Mapping real-time child malnutrition in India using machine learning," Tech. Rep., 2023.
[27] S. Jain, T. Khanam, A. J. Abedi, and A. A. Khan, "Efficient machine learning for malnutrition prediction among under-five children in India," in *2022 IEEE Delhi Section Conference (DELCON)*. IEEE, 2022, pp. 1–10.
[28] S. J. Rahman *et al.*, "Investigate the risk factors of stunting, wasting, and underweight among under-five Bangladeshi children and its prediction based on machine learning approach," *PLOS ONE*, vol. 16, no. 6, p. e0253172, 2021.
[29] F. M. Amin and D. C. R. Novitasari, "Identification of stunting disease using anthropometry data and long short-term memory (LSTM) model," *Computer Engineering and Applications Journal*, vol. 11, no. 1, pp. 25– 36, 2022.
[30] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
[31] S. Hochreiter, "The vanishing gradient problem during learning recurrent neural nets and problem solutions," *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, vol. 6, no. 02, pp. 107–116, 1998.
[32] Y. Bengio, P. Simard, and P. Frasconi, "Learning long-term dependencies with gradient descent is difficult," *IEEE Transactions on Neural Networks*, vol. 5, no. 2, pp. 157–166, 1994.
[33] D. Zhao *et al.*, "A long short-term memory-fully connected (LSTM-FC) neural network for predicting the incidence of bronchopneumonia in children," *Environmental Science and Pollution Research*, vol. 28, no. 40, pp.
[34] 56892–56905, 2021.
[35] M. Athanasiou*et al.*, "Long short-term memory–based prediction of the spread of influenza-like illness leveraging surveillance, weather, and twitter data: Model development and validation," *Journal of Medical Internet Research*, vol. 25, p. e42519, 2023.
[36] S. Yang, H.-C. Chen, C.-H. Wu, M.-N. Wu, and C.-H. Yang, "Forecasting of the prevalence of dementia using the LSTM neural network in Taiwan," *Mathematics*, vol. 9, no. 5, p. 488, 2021.
[37] S. Khare*et al.*, "Investigation of nutritional status of children based on machine learning techniques using Indian demographic and health survey data," *Procedia Computer Science*, vol. 115, pp. 338–349, 2017.
[38] S. R. Vasu, S. Khare, D. Gupta, and A. Jyotishi, *Features Explaining Malnutrition in India: A Machine Learning Approach to Demographic and Health Survey Data*. Singapore: Springer, 2021, pp. 87–99.

[39] H. Verma and S. Kumar, "An accurate missing data prediction method using LSTM based deep learning for health care," in *Proceedings of the 20th International Conference on Distributed Computing and Networking*, 2019.
[40] Z. Mei, C. L. Ogden, K. M. Flegal*et al.*, "Comparison of the prevalence of shortness, underweight, and overweight among US children aged 0 to 59 months by using the CDC 2000 and the WHO 2006 growth charts," *Journal of Pediatrics*, vol. 153, no. 5, pp. 622–628, 2008.
[41] M. De Onis, C. Garza, A. W. Onyango *et al.*, "Comparison of the WHO child growth standards and the CDC 2000 growth charts," *Journal of Nutrition*, vol. 137, no. 1, pp. 144–148, 2007.
[42] I. M. Aris, S. L. Rifas-Shiman, L.-J. Li *et al.*, "Association of weight for length vs body mass index during the first 2 years of life with cardiometabolic risk in early adolescence," *JAMA Network Open*, vol. 1, no. 5, p. e182460, 2018.
[43] R. Sendra-Arranz and A. Gutierrez, "A long short-term memory artificial´ neural network to predict daily HVAC consumption in buildings," *Energy and Buildings*, vol. 216, p. 109952, 2020.
[44] X. Gu*et al.*, "The sliding window and SHAP theory—an improved system with a long short-term memory network model for state of charge prediction in electric vehicle application," *Energies*, vol. 14, no. 12, p. 3692, 2021.
[45] D. S. Freedman, A. J. Goodwin-Davies, L. Kompaniyets*et al.*, "Interrelationships among age at adiposity rebound, BMI during childhood, and BMI after age 14 years in an electronic health record database," *Obesity*, vol. 30, no. 1, pp. 201–208, 2022.
[46] C. B. Vennerød, A. Kjærran, and E. S. Bugge, "Long short-term memory RNN," *arXiv preprint arXiv:2105.06756*, 2021.
[47] M. Pirani, P. Thakkar, P. Jivrani, M. H. Bohara, and D. Garg, "A comparative analysis of ARIMA, GRU, LSTM, and BiLSTM on financial time series forecasting," in *2022 IEEE International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE)*. IEEE, 2022, pp. 1–6.