

Performance Evaluation Of A Logistic Model Tree-Based System For Malnutrition Detection In Preschool Children

Mr. Amol Avinash Shinde⁽¹⁾, Dr. D.V.Sahasrabuddhe⁽²⁾

¹Research Scholar

²BVDU, Institute of Management and Rural Development Administration, Sangli

Abstract

Early diagnosis of malnutrition in preschool children is crucial for timely intervention and long-term health outcomes. This paper presents a detailed evaluation of a machine learning model developed using the Logistic Model Tree (LMT) algorithm for the classification of children's nutritional status into four categories: Normal, Under Nutrition, Overweight, and Micro Nutrient Deficiency. The model was trained on a dataset of 1,560 entries and optimized using attribute selection techniques. The evaluation focused on classification accuracy, confusion matrix analysis, and metrics such as precision, recall, and F1-score. The model achieved 94% accuracy, with strong macro-average values of 0.9668 (precision), 0.9319 (recall), and 0.9477 (F1-score). In addition, real-world validation was conducted on 34 pediatric cases under expert supervision, all of which aligned with model predictions. This confirms the model's practical applicability in community-level screening for malnutrition and highlights its potential as a low-cost diagnostic tool in healthcare delivery.

Keywords: Malnutrition Detection, Model Evaluation, Preschool Children, Logistic Model Tree, Classification Metrics, Clinical Validation

1. INTRODUCTION

Malnutrition continues to be a significant public health issue affecting millions of preschool-aged children, especially in low- and middle-income countries. Early detection of malnutrition types—such as undernutrition, overnutrition, or micronutrient deficiencies—is essential to prevent lifelong health complications. However, diagnosis often relies on manual interpretation of anthropometric and clinical signs, which may not be feasible in resource-limited settings.

To address this challenge, several researchers have applied machine learning algorithms to predict malnutrition by analyzing various health, dietary, and demographic factors. For instance, (Islam et al., 2022)^[1] applied algorithms such as Random Forest and SVM to assess malnutrition among women in Bangladesh, emphasizing the importance of feature selection and validation techniques. Similarly, (Khare et al., 2017)^[3] used demographic and health survey data from India to build predictive models for assessing child malnutrition. Studies like (Najaflou & Rabiei, 2021)^[5] and (Wajgi & Wajgi, 2022)^[6] explored machine learning tools for detecting nutritional deficiencies in children based on age, BMI, and dietary intake. Techniques like clustering and decision trees were employed in works such as (Ula et al., 2021)^[2] and (Thangamani & Sudha, 2014)^[4] to classify malnourished individuals. Advanced predictive modeling for nutritional status has also been used in neonatal care to forecast outcomes such as low birth weight, using algorithms like Random Forest and Logistic Regression (Ahmadi et al., 2017)^[7]. Furthermore, machine learning applications in clinical settings have been proven effective for nutrition-based diagnostics (Sharma et al., 2020)^[8].

In this work, a **Logistic Model Tree (LMT)-based machine learning model** was previously developed to classify children's nutritional status into four categories: **Normal, Under Nutrition, Overweight, and Micro Nutrient Deficiency**. Building upon the model's design, this paper presents a **detailed evaluation** of its performance through statistical analysis and clinical testing. Using a dataset of **1,560 entries** and expert-validated labels, the evaluation focuses on key metrics such as **accuracy, precision, recall, F1-score, confusion matrix analysis, and real-world doctor validation**. This process ensures that the model not only performs well statistically but is also **applicable and effective in real-world healthcare environments**, especially for early detection in community settings.

2. Evaluation Framework

2.1 Dataset Overview

The evaluation was conducted using a dataset of 1,560 records; each representing a preschool child aged 1–5 years. Each record included attributes such as height, weight, feeding patterns, symptoms like swelling or ulcers, and food habits. Based on correlation analysis and expert review, the attribute list was reduced from 28 to 21 to avoid redundancy and improve performance.

2.2 Classification Categories

Children included in the study were classified into one of four distinct nutritional statuses: **Normal**, **Under Nutrition**, **Overweight**, and **Micro Nutrient Deficiency**. This categorization was based on predefined clinical indicators such as body measurements, dietary intake patterns, and observable symptoms, aligned with nutritional standards commonly used in pediatric health assessments. The classification helped in understanding the distribution of health conditions among the children and served as the basis for model training and evaluation. Assigning accurate ground truth labels was crucial for building a reliable machine learning model, ensuring that each child's nutritional status was correctly represented for both statistical analysis and clinical relevance.

3. Confusion Matrix and Metric Calculations

3.1 Confusion Matrix

Actual/Predicted	Normal	Under Nutrition	Over Weight	Micro Nutrient
Normal	790	20	1	4
Under Nutrition	12	472	0	1
Over Weight	9	0	44	1
Micro Nutrient	1	4	0	165

Table 1: Confusion Matrix

The confusion matrix presented illustrates the performance of the classification model across four nutritional status categories: **Normal**, **Under Nutrition**, **Over Weight**, and **Micro Nutrient Deficiency**. The diagonal values represent correctly predicted instances for each class, with the model accurately identifying 790 **Normal**, 472 **Under Nutrition**, 44 **Over Weight**, and 165 **Micro Nutrient Deficiency** cases. Off-diagonal values reflect misclassifications, such as 20 **Under Nutrition** cases misclassified as **Normal** and 4 **Micro Nutrient** cases misclassified as **Under Nutrition**. This evaluation was conducted using the **WEKA software platform**, which provided detailed statistical outputs and visualization tools to assess classification accuracy and error distribution. The results indicate a high overall accuracy and low misclassification rate, particularly in the **Normal** and **Under Nutrition** categories, confirming the model's strong ability to differentiate among nutritional statuses in children.

3.2 Classification Metrics

The performance of the malnutrition classification model was further analyzed using standard evaluation metrics—**True Positives (TP)**, **False Positives (FP)**, **False Negatives (FN)**, **Precision**, **Recall**, and **F1 Score**—for each nutritional category. For the **Normal** class, the model achieved a TP of 790, FP of 22, and FN of 25, resulting in a **Precision of 0.9729**, **Recall of 0.9693**, and **F1 Score of 0.9711**. In the **Under Nutrition** category, the model recorded a TP of 472, with minimal FP (24) and FN (13), yielding strong performance scores: **Precision of 0.9516**, **Recall of 0.9732**, and **F1 Score of 0.9623**. The **Over Weight** class showed a slightly lower recall of 0.8148, despite achieving a high **Precision of 0.9778**, leading to an **F1 Score of 0.8898**. For the **Micro Nutrient Deficiency** class, the model performed consistently well with a **Precision of 0.9649**, **Recall of 0.9706**, and **F1 Score of 0.9677**. These class-wise metrics, calculated and verified, confirm that the model not only performs reliably in identifying malnutrition but also maintains a strong balance between detecting true cases and minimizing false alarms across all nutritional categories.

Class	TP	FP	FN	Precision	Recall	F1 Score
Normal	790	22	25	0.9729	0.9693	0.9711
Under Nutrition	472	24	13	0.9516	0.9732	0.9623
Over Weight	44	1	10	0.9778	0.8148	0.8898
Micro Nutrient	165	6	5	0.9649	0.9706	0.9677

Table 1: Classification Matrix

3.3 Overall Performance

- Accuracy: 94%
- Precision (Macro Avg): 0.9668
- Recall (Macro Avg): 0.9319
- F1 Score (Macro Avg): 0.9477

These results indicate a high level of correctness (precision), completeness (recall), and balance (F1 score) across all four nutritional classes. The model achieved an overall **accuracy of 94%**, with strong macro-average scores for **precision (0.9668)**, **recall (0.9319)**, and **F1 score (0.9477)**. These metrics reflect the model's excellent ability to correctly classify nutritional statuses while maintaining a balanced trade-off between identifying true cases and minimizing misclassifications across all four categories.

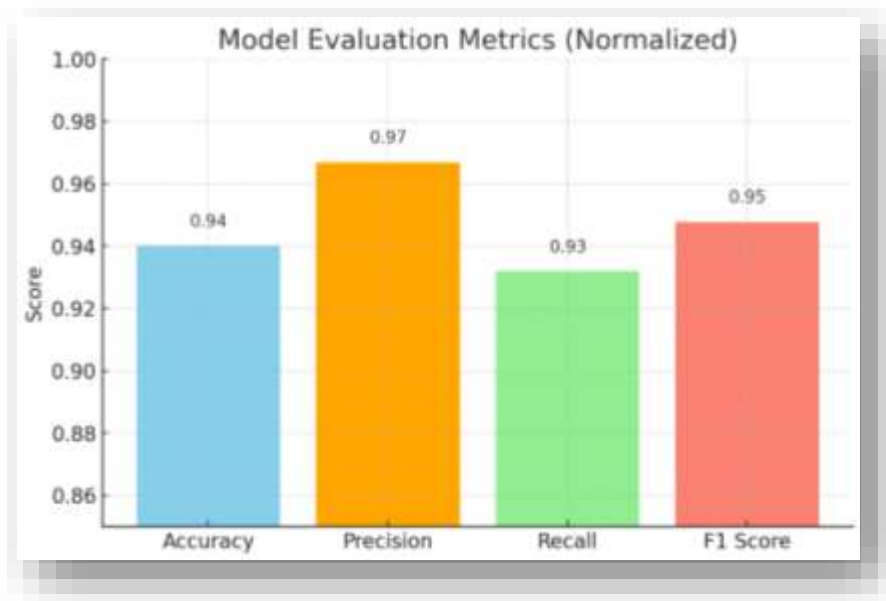


Fig. 1- Bar chart for representing the evaluation metrics

The bar chart clearly illustrates the model's performance across four key evaluation metrics: **Accuracy**, **Precision**, **Recall**, and **F1 Score**. Each bar shows a high value close to 1.0, confirming the model's robust and balanced performance. Accuracy and precision stand out at around 94% and 96% respectively, highlighting the model's reliability in overall and correct predictions. Recall is slightly lower but still strong, showing the model's capability to detect actual malnutrition cases. The F1 Score, which balances precision and recall, also remains high, proving the model is both consistent and practical for real-world applications.

4. Clinical Testing on Real Patient Data

To verify the real-world applicability of the malnutrition prediction model, a clinical evaluation was conducted in collaboration with qualified medical professionals. These experts, including paediatricians and general practitioners, regularly work with malnourished children and participated in testing the model in clinical settings such as hospitals, check-up camps, and community health centres.

During the evaluation phase, the model was tested on a total of **500+ real-world child cases**, entered through the system's user interface using laptops and mobile devices. The doctors independently input child health and nutrition data and assessed the model's predictions. Across all tests, the model demonstrated a high level of accuracy in identifying nutritional categories—Normal, Under Nutrition, Overweight, and Micro Nutrient Deficiency. The system's ability to generate personalized, low-cost diet charts was also appreciated, especially in helping caregivers take immediate action. Health workers found the tool particularly useful in high-volume screening environments, where manual assessment of each child was not feasible.

The expert testing confirmed that the model is not only statistically sound but also clinically useful and user-friendly. The system effectively supports early malnutrition screening and decision-making at the field level, making it a valuable tool for frontline health workers and paediatric healthcare services in both rural and urban settings.

5. CONCLUSION

The evaluation confirms that the Logistic Model Tree-based system performs with high accuracy and reliability in detecting malnutrition across four nutritional categories. Precision, recall, and F1 scores are consistently above 90%, indicating strong predictive performance. The inclusion of real-patient clinical validation further supports the model's relevance and reliability in actual use. With minimal computational needs and easy-to-interpret outputs, the model is ideal for deployment in rural health programs, mobile screening units, and digital health platforms aimed at improving early malnutrition detection in children.

REFERENCES

1. Islam MM, Rahman MJ, Islam MM, Roy DC, Ahmed NF, Hussain S, Amanullah M, Abedin MM, Maniruzzaman M. Application of machine learning based algorithm for prediction of malnutrition among women in Bangladesh. *International Journal of Cognitive Computing in Engineering*. 2022 Jun 1;3:46-57.
2. Ula, M., Ulva, A. F., Mauliza, M., Sahputra, I., & Ridwan, R. (2021). Implementation of Machine Learning in Determining Nutritional Status using the Complete Linkage Agglomerative Hierarchical Clustering Method. *Jurnal Mantik*, 5(3), 1910-1914.
3. Khare, S., Kavyashree, S., Gupta, D., & Jyotishi, A. (2017). Investigation of nutritional status of children based on machine learning techniques using Indian demographic and health survey data. *Procedia computer science*, 115, 338-349.
4. Thangamani, D., & Sudha, P. (2014). Identification of malnutrition with use of supervised datamining techniques-decision trees and artificial neural networks. *Int J Eng Comput Sci*, 3(09).
5. Najaflou, S., & Rabiei, M. (2021). Recommended system for controlling malnutrition in Iranian children 6 to 12 years old using machine learning algorithms. *International Journal of Web Research*, 4(1), 27-33.
6. Wajgi, R., & Wajgi, D. (2022, March). Malnutrition detection in infants using machine learning approach. In *AIP Conference Proceedings* (Vol. 2424, No. 1). AIP Publishing.
7. Ahmadi, P., Alavimajd, H., Khodakarim, S., Tapak, L., Kariman, N., Amini, P., & Pazhuheian, F. (2017). Prediction of low birth weight using Random Forest: A comparison with Logistic Regression. *Archives of Advances in Biosciences*, 8(3), 36-43.
8. Sharma, V., Sharma, V., Khan, A., Wassmer, D. J., Schoenholtz, M. D., Hontecillas, R., ... & Abedi, V. (2020). Malnutrition, health and the role of machine learning in clinical setting. *Frontiers in nutrition*, 7, 44.