

A Machine Learning Model for Malnutrition Detection in Preschool Children

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ABSTRACT

The use of artificial intelligence techniques has introduced a new dimension to the health-care sector, particularly in diagnosing diseases in their early stages, allowing patients and health-care workers to take early corrective action. The study discusses a machine learning algorithm created to detect and classify malnutrition in preschool children. Malnutrition affects a significant number of children in various nations, many of whom are preschoolers. Early identification of malnutrition in a preschool child will allow parents to monitor the child's health. The model also proposes dietary plans based on the type of malnutrition diagnosed.

Introduction -Between the ages of one and five, children start to develop new diet habits, often influenced by exposure to new tastes and market foods. It can lead to health issues like obesity or insufficient nutritional intake. Malnutrition can arise from food that does not meet a child's nutritional needs or from an imbalanced diet. Early identification and treatment are crucial to avoid long-term health problems affecting the child's overall development. A well-balanced diet is vital to prevent diseases and chronic health conditions. Parents try to provide adequate nutrition, but deficiencies in early development stages can cause stunted growth, weakened immunity, and other issues.

Objectives- The primary aim is to develop a machine learning model that can detect and classify malnutrition in preschool children early. By predicting malnutrition, the model assists parents in taking preventive actions and managing their child's health effectively. Additionally, the model proposes personalized dietary plans based on the diagnosed type of malnutrition. It also emphasizes providing a simple, questionnaire-based system for remote or rural parents, making healthcare advice easily accessible.

Methods -The development of model was like Exploratory Data Analysis (EDA), attribute selection, model selection, model training, and evaluation. Initially, twenty-eight attributes were shortlisted based on clinical and nutritional research, and then reduced to twenty-one essential attributes. Various machine learning algorithms were tested using the WEKA tool, and Logistic Model Tree (LMT) was selected for its high accuracy. The model was trained with 70% of the dataset and tested with 30%. A two-phase model implementation was done to first detect malnutrition and then to classify the type (undernutrition or micronutrient deficiency).

Results

The Logistic Model Tree (LMT) achieved an accuracy of 91% in detecting malnutrition. A two-step diagnosis improved the detection of undernutrition and micronutrient deficiencies. Grouping attributes related to medical and dietary factors further increased the accuracy to 95% in the second phase. The model successfully classified preschool children as healthy, undernourished, over-nourished, or suffering from micronutrient deficiencies, and suggested appropriate dietary plans based on the diagnosis.

Conclusions

The application of machine learning models in healthcare supports early intervention and

better health outcomes. The developed model accurately predicts malnutrition in preschoolers and provides a user-friendly platform for parents, especially those in remote areas. By suggesting customized diet plans, the model helps parents manage their child's nutritional needs effectively, reducing the risk of long-term health problems.

Keywords: Feature selection, Machine Learning Model, Healthcare, Malnutrition and Nutrition.

1. INTRODUCTION

Between the ages of one and five, child starts to develop new eating habits, which are frequently impacted by his exposure to new tastes of market food. Higher risks of obesity or insufficient nutritional intake are just two of the health issues that might result from these shifting habits. Malnutrition can arise from food that does not satisfy a child's nutritional needs or from an imbalance in their diet; in order to avoid long-term health problems, malnutrition should be identified and treated as early as feasible to avoid its impact on overall development of him.

A well-balanced diet is essential for avoiding severe health issues like diseases and chronic ailments. Parents endeavour to provide their child with appropriate diet, but when child does not obtain adequate food during his early development phases, he may encounter a variety of health difficulties. These issues can include stunted growth, wasting, underweight, and a weaker immune system (Gadekallu, 2021)[2]. Proper nutrition is essential for a child's survival and development, especially in the preschool age range (1-5 years), when nutritional requirements are particularly high.

According to the World Health Organization (WHO) [9], about 45 million children under the age of five suffer from severe wasting, which is linked to poor nutrition and may lead to related diseases.

According to the Global Hunger Index (2024)[10], India ranks 105th with a score of 27.3, underlining the need for urgent action to alleviate malnutrition and hunger.

Organizations like ASPEN are attempting to address this issue by managing associated illnesses and fighting malnutrition. Furthermore, the diagnosis of malnutrition is one of the healthcare applications for cutting-edge technology like machine learning. Early intervention and better health outcomes are made possible by this technology's ability to detect changes in a child's nutritional condition.

The study presents a machine learning algorithm that can identify the sort of malnutrition a child may be experiencing and provide a diet plan to treat it. The approach allows parents to complete a straightforward questionnaire that includes questions about eating habits, basic health metrics that parents can readily respond, and as a model's output gets the diagnosis and diet plan, if the kid is malnourished.

2. RELATED WORK

The evaluation of various machine learning models for predicting malnutrition has identified several characteristics and techniques to enhance accuracy, particularly in resource-limited environments. Socioeconomic factors, maternal education, cleanliness, access to healthcare, and eating patterns are commonly recognized attributes. For instance, maternal education and socioeconomic status were found to be significant predictors of malnutrition by Khare et al. (2017) [3] and Fenta et al. (2021) [4]. Similarly, BMI, MUAC, and household income served as critical variables to predict nutritional outcomes according to Islam et al. (2022) [1] and Najafloo and Rabiei (2021) [5]. Furthermore, research by Mawa and Lawoko (2018) [7] and Babatunde et al. (2011) [8] highlighted the importance of food diversification and cleanliness in forecasting nutritional status.

Numerous machine learning models have used various classification algorithms like decision trees, random forests, support vector machines (SVM), artificial neural networks (ANNs), gradient boosting, and convolutional neural networks (CNNs). Because of its great accuracy and capacity to handle complex data, random forests and gradient boosting were frequently employed. For instance, random forests were shown to be especially useful in the classification of malnutrition by Islam et al. (2022) [1] and Fenta et al. (2021) [4]. (Gadekallu, 2021)[2] CNNs were creatively used for facial feature analysis to make non-invasive predictions about malnutrition. Both SVM and ANNs performed well in studies such as Sharma et al. (2020) [6], where ANNs were the most accurate in predicting the effects of malnutrition based on medical records.

3. MACHINE LEARNING MODEL FOR MALNUTRITION PREDICTION-

A structured development approach begins with problem formulation and progresses via Exploratory Data Analysis (EDA). In this approach developers attempt to generate insights from collected and pre-processed data helping in developing effective, scalable, and sustainable machine learning model. Under EDA steps undertaken are attribute selection, model selection, and model training. To achieve the best possible outcomes, the trained model must be assessed and adjusted before to deployment. The processes of model selection and evaluation are thoroughly covered in the study. In the sections that follow, the EDA and attribute selection steps are described for reference.

3.1 Initial Stage of development of model - Attribute Selection-

Attribute selection is frequently the first step in development of a machine learning model to identify malnutrition. This is important since the model's capacity to learn efficiently and generate precise predictions is directly impacted by attributes (or qualities) chosen. From the prior study twenty eight pertinent attributes that might affect the diagnosis of malnutrition were listed. Clinical knowledge, medical records, and nutritional research are probably the sources of these qualities.

The list of attributes was whittled down to Twenty One essential attributes that were most pertinent for identifying malnutrition following expert consultation and the application of Exploratory Data Analysis (EDA) techniques like correlation analysis, PCA and dependency. These characteristics include a mix of demographics, physical characteristics, medical history, eating patterns, and certain nutritional elements that are detailed in Table 1 below.

Demographic Factors	Physical Measurements	Health History	Dietary Habits And Specific Nutritional Factors
• Gender • Age	• Height • Weight • Head Circumference • Mid-Upper Arm Circumference • Pinch Test	• Feeding Duration • Birth dieses • Swelling • Frequency of Mouth Ulcer	• Feeding • Milk (Cow/Buffalo/Goat) • Rice • Lentils • Clarified Butter (Ghee) • Semolina • Fruits • Egg • Nonveg • Any other Food

Table 1 : List and Categories of Attribute

3.2 Model Selection-

The problem is of supervised learning specifically classification and hence the algorithms considered for implementation were classification algorithms. Considering the type of data, the intricacy of the issue, and the intended result all influence the model choice. Through experimentation, the best model that fits the data and the problem can be chosen with more precision.

Using the "WEKA tool," various algorithms were applied to the sample data of 560 patients in order to determine whether or not the child was malnourished. Five algorithms with an accuracy of up to 75% are listed in Table 2.

Sr.No.	Algorithm Name	Accuracy
1	Logistic Model Tree (LMT)	91%
2	Simple Logistic	91%
3	Random Forest	89%
4	J48	85%
5	Random Tree	78%

Table 2 : Tested Algorithms with Accuracy

The aforementioned algorithms were tried to determine whether or not the youngster was malnourished. The "LMT" algorithm was chosen for the model's implementation after taking into accounts the data's pattern and algorithm correctness and the most prominent feature of the algorithm that combines decision tree learning with logistic regression, creating a classification model that leverages both the interpretability of trees and the predictive power of logistic regression which helps in improving accuracy as the size of data considered for model goes on increasing [11]. Diagram 1 show the tree generated after execution of LMT algorithm. In this tree only four attributes we have considered to make the figure readable –

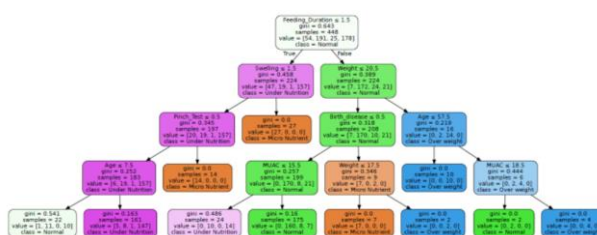


Diagram 1 : LMT generated for four attributes

3.3 Model Training-

The finalizing the algorithm for model, next phase was to train the model to get best results. For training the model the entire data was divided in two sets training set (70% records) and rest of data was used for testing (30% records). When the model was executed using two sets same results were given as in model selection phase.

However, diagnosing malnutrition alone was insufficient; the next step was to determine type of the malnutrition- undernutrition, micronutrient deficiencies, or over nutrition. The following are descriptions of these three forms of malnutrition:

- **Undernutrition:** The kid experiences stunting (low height for age), underweight (low weight for age), or wasting (low weight for height).
- **Over nutrition:** The child is fat and may have obesity-related disorders.

- **Micronutrient deficiencies:** The child lacks essential vitamins and minerals such thiamine (vitamin B1), niacin (vitamin B3), and vitamin C.

Although the twenty one attributes mentioned above were used to diagnose over nutrition with ease, it is extremely difficult to determine whether a kid is experiencing undernutrition or micronutrient deficiencies due to a very thin line of difference between two. The algorithm's accuracy in predicting whether it was undernutrition or micronutrient deficiencies was consequently impacted.

Diagram 2 illustrates the two levels at which the model was implemented in order to increase the accuracy of the results for the prediction of the type of malnutrition. The diagnosis will be made in two steps.

Step I: Assessing for adequate or unhealthy nutrition

Step II: Look for "undernutrition" or "micronutrient deficiencies" if the child is diagnosed with malnutrition.

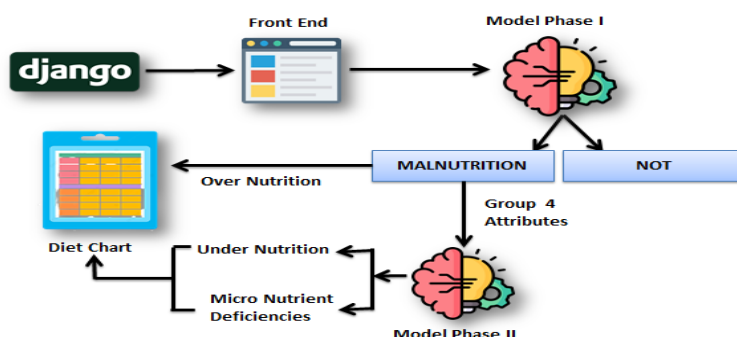


Diagram 2 : Implementation of Model in Two Phases

The data is sent to the second step, which employs the same algorithm but now focuses exclusively on attributes from two groups— physical measurements and food habits— to diagnose if it undernutrition or micro nutrient.

3.4 Model Evaluation and Tuning-

The accuracy of detecting malnutrition types such as undernutrition and micronutrient deficiencies was found to be impacted by the trained model's evaluation for predicting malnutrition type based on all 21 variables. As indicated in Table 3 below, the input data was split up into various groups in order to fine-tune and increase the accuracy of identifying the type of malnutrition.

Group No.	Attributes
1	Demographic factors, Height, Weight, Feeding Duration, Birth Disease
2	Demographic factors, Height, Weight, Mid-Upper Arm Circumference, Head Circumference, Pinch Test, Swelling, frequency of Mouth Ulcer
3	Demographic factors, Height, Weight, Dietary habits
4	Demographic factors, physical measurements, Swelling, frequency of Mouth Ulcer, Dietary information
5	Demographic factors, physical measurements, health history
6	Demographic factors, Height, Weight, Feeding Duration, Birth Disease, Dietary Information

Table 3 : Attributes Division in Groups

Once the child is diagnosed with malnutrition rather than over nutrition, then the challenge is to check whether the child is suffering with **undernutrition or micronutrient deficiencies**. The model was trained and tested for accuracy considering different group attributes. Table 4 represents the accuracies for all attributes and group attributes.

Sr. No.	Attributes	Accuracy (%)
1	All Attribute	91
2	Group 1	84
3	Group 2	93
4	Group 3	87
5	Group 4	95
6	Group 5	86
7	Group 6	87

Table 4 : Accuracy for Different Groups of Attributes

Accuracy for attributes in Group 4 which considers Medical and Food Information gives better accuracy for checking under nutrition or micronutrient deficiencies. Hence for implementation of the model we have finalized to consider attributes from Group 4 as input to phase II while checking for type of malnutrition as under nutrition or micronutrient deficiencies.

4. Model Implementation-

It is always preferred if the prediction model is given with open access over the public network for the convenience of parents. Hence the model's Graphical User Interface (GUI) was implemented using Django, a robust web framework for developing effective input and output. At the back of Django framework Machine Learning Model is executed on the input data which generates output as either Healthy or type of malnutrition detected along with the personalized diet suggestions which is discussed in section 4.1 and 4.2 respectively.

4.1 Model Inputs-

The main goal of the study is to assist parents who live in remote locations with limited access to healthcare facilities or who want to monitor their child's progress. The concept is created and used in Marathi, the regional language of Maharashtra, India. Figure 1 below illustrates how parents can provide input to the model using a questionnaire. The majority of the questions are self-descriptive and are yes/no in nature, making them simple for parents to comprehend and respond to.

Figure 1 displays the user interface for the questionnaire.

Children Malnutrition Prediction Model		
1	Gender	☒ Male ☐ Female
2	Age	Month
3	Height	C.M.
4	Weight	K.G.
5	Duration of breastfeeding the child	6 Month v
6	Does the child have a congenital disease?	☒ Yes ☐ No
7	Child's middle arm circumference	C.M.
8	Child's head circumference	C.M.
9	Child's pinch test	☒ Skin regenerates (in 2 seconds) ☐ Skin does not regenerate (within 2 seconds)
10	Does the child frequently have swelling on his body? And to what extent?	Yes, it comes in lar v
11	Is frequent mouth sores a problem for a child? And to what extent?	Yes, twice a month v
12	Which of the following types of food are you giving to your child?	
A)	Mother's breast feeding	☒ Yes ☐ No
B)	Cow/buffalo/goat milk	☒ Yes ☐ No
C)	Rice	☒ Yes ☐ No
D)	Lentils	☒ Yes ☐ No
E)	Clarified Butter (Ghee)	☒ Yes ☐ No
F)	Semolina	☒ Yes ☐ No
G)	Fruits	☒ Yes ☐ No
H)	Eggs	☒ Yes ☐ No
I)	All other foods	☒ Yes ☐ No
J)	All other non-vegetarian foods	☒ Yes ☐ No
SUBMIT		

Figure 1- Model Input

4.2 Model Output-

Figure 2 shows the model's output along with the personalized diet plan depending on the type of malnutrition.

The imported data from Django form input data is sent to the model for analysis. As seen in Figure 2 below, the model analyses the data and forecasts the user's nutritional state.

In the event "over-nutrition," the system instantly creates and presents a diet plan to assist the user in controlling their weight and maintaining a healthy diet. Recommendations like cutting back on high-calorie foods, consuming more fibre, and continuing an appropriate exercise regimen may be part of the diet plan.

However, the system moves on to a more thorough examination if the model predicts "under-nutrition" or "micro-nutrition deficiency." In this instance, Group 4 data was once more sent to the model for additional evaluation. This extra step guarantees that the model can improve its forecasts and offer a more precise assessment of the user's nutritional status.

The ML model generates a final, refined output that precisely classifies the user's nutritional state after processing the extra parameters. The system creates a comprehensive food plan that is especially designed to correct undernutrition or micronutrient deficiencies based on this improved forecast. To help the user get optimal nutrition, the diet plan offers meal plans, nutrient-rich food selections, and further guidelines.

Lastly, the user is presented with the created diet plan via the front-end interface. In order to enhance their health, users can read their customized nutrition advice, which includes meal ideas, portion amounts, and other lifestyle suggestions.

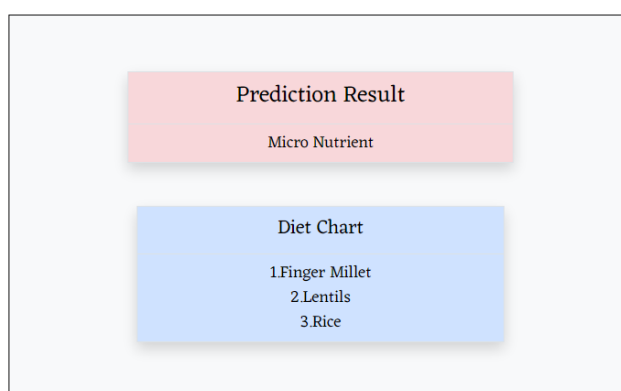


Figure 2- Model Output

5. CONCLUSION

The use of machine learning models in the healthcare sector to make early decisions helps patients and healthcare professionals take preventative action. Predicting malnutrition in preschoolers is more accurate with the model covered in the article. Parents may easily take care of their child's health thanks to the user interface. The model also makes dietary recommendations for the child based on the diagnosis, which helps parents prevent things from getting worse over time.

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