Data Mining Based Prediction of Malnutrition in Afghan Children

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Abstract— Proper nutrition is an essential component for the survival, growth, and development of children in society. Malnutrition is a global problem in today's life. The primary target of this phenomenon is children under five years of age and mostly for developing countries. In this study, a data mining approach is proposed to predict the malnutrition status of children under five years of age in Afghanistan. Random Forest, PART rule induction, and Naïve Bayes classifiers were applied to Afghanistan Nutrition SMART Survey data. The results were compared with Logistic Regression statistical method. Random Forest and PART rule induction classifiers performed well with the highest accuracy for stunted, underweight, wasted, and nutritional oedema statuses with and without transformed attributes. This study defines how data mining classification techniques can classify malnutrition status for children under five years of age. Generally, our method was the one that obtained the most robust results to predict the malnutrition status based on clinical sign and anthropometric parameters of preschool-age Afghan children.

Keywords— Malnutrition, Under five children, Nutritional Oedema, Data Mining, SMART Survey Dataset.

I. INTRODUCTION

Proper nutrition is a vital component for survival, growth, and development of children in society. In today's life, malnutrition is a global problem in the healthcare world. The primary target of this worldwide phenomenon are children under five years of age from across the globe. Presently, about half of the under five years of age children's mortality is concerned with undernutrition [1].

In 2018, 49 million children under five years of age were globally wasted, while the overweight was estimated at 40 million in the world. In Asia in 2018, there was evidence that more than half of all stunted children under five years of age that contributed 55% of all children affected in the world; while 39% of them lived in Africa. Likewise, Asia contributed 68% of wasted children in the world [2].

The term malnutrition can be used for all forms of bad nutrition; mainly, it consists of either undernutrition or overnutrition [3]. Undernutrition is widespread in preschool-age children. We can define undernutrition as a lack in the amount of essential proteins and nutrients that are the primary requirements for proper growth [4]. Undernutrition consists of the interrelated measure of wasted, underweight, and stunted caused by deficiencies of essential vitamins and minerals [5]. Stunted is an indicator of chronic malnutrition comes from the result of long-term food shortage; wasted indicates the acute malnutrition that occurs when the child is faced with the lack of recent food, and underweight is the composite indicator for both acute and chronic malnutrition [6].

Undernutrition is associated with many diseases such as digestion, and absorption that affect various groups, including children under five years of age, adolescents, Pregnant and Lactating Women (PLW), and the elderly. As children depend entirely on others, and they are particularly vulnerable [7].

Among developing countries, Afghanistan is one of the countries which attains the highest grade of stunted in children under five years of age. For over several decades the Afghan people have suffered from civilian wars. Critically, the country has the highest maternal mortality rank in the world. The statistic proves, that war causes health facilities to be inaccessible to the majority the population. These barriers had a direct impact on the children's nutritional ecosystem. Moreover, wasted is also remarkably high for children under five years of age in Afghanistan [8].

Across Afghanistan, in 22 out of 32 provinces, children under five years of age are suffering from acute malnutrition at an emergency level. Severe acute malnutrition is alarming, and about two million children under five years of age are affected each year [9].

The study of malnutrition in children under five years of age is a demandable choice in a new research area. Attempts have been made in recent years to identify the determinants of malnutrition and provide an up-to-date situation of malnourished children under the age of five and PLW in Afghanistan [10,11,12]. Based on their findings, Afghanistan was in the critical situation for children and PLW mortality and morbidity. Furthermore, all studies [13, 14, 15] used statistical models. But none of the studies explored the nutritional data to apply predictive models using data mining techniques to predict the malnutrition status based on the significant risk factors. Therefore, the goal of this study is to classify the malnutrition status of children from birth to 59 months old using data mining algorithms.

The rest of this paper is organized as follows. Section II briefly describes the current assessment method for malnutrition in Afghanistan. In Section III, related work is discussed, and the study methodology is described in Section IV. Last, Sections V and VI discuss the result and discussion, and our conclusion is drawn in the final section.

II. MALNUTRITION ASSESSMENT IN AFGHANISTAN

The aim of malnutrition assessment in children under five years of age is to define whether a child is in undernutrition,

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overnutrition, or normal status. The assessment process performs systematically. In Afghanistan, this assessment for preschool-age children presents in two systematic ways: clinical signs and anthropometric parameters.

A. Nutritional Oedema

Oedema is the preservation of water in the tissues of the body. Oedema is a clinical sign considered as severe acute malnutrition, and it is a dangerous form of undernutrition. Oedema is classified based on its severity, including a) mild oedema grade (+) is bilateral pitting oedema in both feet, b) moderate oedema grade (++), emerges in bilateral pitting of feet and lower limbs/hands, and c) severe oedema grade (+++), emerges in feet, lower limbs/hands, and periorbital area (puffy eyes). For this study, only grade (+) was considered. Because the nutritional oedema is always identified by bilateral pitting in both feet of child. On the other hand, the nutrition data has only grade (+) oedema and other classes may cause other diseases [16].

B. Anthropometric Measurements

Anthropometric measurement is consisting of measuring the height, weight, and Mid-Upper Arm Circumference (MUAC) for children under five years of age. MUAC is used for the children from 6-59 months. The standard anthropometric indices are weight-for-height, height-for-age, weight-for-age, and MUAC. These indices are very common in Afghanistan. These indices are formulated based on WHO 2006 growth standards [16].

III. RELATED WORK

Recently, a number of data mining and machine learning algorithms were employed to extract the hidden patterns from nutritional data in the healthcare industry. The main objective of these techniques is to provide useful information for decision makers and policymakers in the healthcare industry, which can help to provide a better determination of malnutrition status in the target population, particularly in children under five years of age group. At present, data mining and machine learning are significant contributors in terms of predicting and analyzing the outcomes of malnourished patients.

Various supervised and unsupervised techniques are applied to classify and identify malnutrition status for the different population groups. A logistic regression model was used to discover the malnutrition hidden patterns from Indian Demographic and Health Survey (IDHS) data, considering four major anthropometric indices weight-for-height, weight-for-age and height-for-age [17]. Likewise, a logistic regression model was applied to Bangladesh Demographic and Health Survey (BDHS) of 2004 to classify chronic malnutrition of children under five years of age [18]. A deep learning approach ANN is applied to BDHS 2014 to classify the malnutrition status of children between the ages of 0-59 months [19].

Low birth weight is one of the crucial risk factors of malnutrition in infants. In [20], a research was conducted to predict low birth weight and its associated risk factors using Support Vector Machine (SVM), Neural Network, Naïve Bayes, Random Forest, and Decision Tree algorithms. A decision tree classification method was applied to a DHS the case study in Sri Lanka to generate the rules for identifying malnutrition status in children under five years of age [21].

Decision Tree, SVM, Bayesian Network, Decision Rule, and Nearest Neighbor were applied to predict whether a malnourished patient needs to be followed by a nutrition specialist or not [22]. PART and Naïve Bayes algorithms were used on the Ethiopia Demographic and Health Survey (EDHS) data to predict the malnutrition status of preschool-age children [23]. Artificial Neural Network (ANN) and decision tree were applied to Indian family health survey data to predict the malnutrition status of children aged under five years based on their food intake [24]. ANN with backpropagation method was used to predict the malnutrition types (marasmus, kwashiorkor, and marasmus-kwashiorkor) based on symptoms in children [25].

K-Means clustering is one of the most straightforward unsupervised data mining algorithms which is widely implemented in medical science. A K-Means clustering technique was employed to build an intelligent application to identify the nutritional status of toddlers in Indonesia [26].

As stated in the above literature, various algorithms of data mining and machine learning were applied to healthcare data to present knowledgeable and useful consequences for domain area experts. As outlined in the literature, most of these studies have only focused on anthropometric indicators of malnutrition for predicting malnutrition status of children under five years of age. On the other hand, some of the reviews just relied on statistical models. Our research potentially considered both the anthropometric indicators and the clinical sign (bilateral pitting oedema) to predict the malnutrition status of the Afghan children using well-known data mining classification algorithms.

IV. METHODOLOGY

Data mining is responsible for finding unknown and hidden patterns in an extensive amount of data to extract useful information. The purpose of this study is to discover unseen information from Afghanistan's Nutrition Standardized Monitoring and Assessment of Relief and Transitions (SMART) survey data. The proposed method for this study is depicted in Fig.1. Our method consists of problem domain understanding, data understanding, data preparation, data mining, and evaluation, which are the major steps of the Knowledge Discovery Process (KDP) [27].

A. Problem Domain Understanding

In this step, to understand the problem domain, many discussions have initiated with the domain experts and an in-depth study of related articles and books performed. Furthermore, observations and meetings have conducted with local health centers, local health workers, and community-based health workers who were involved in the nutrition services for the target population.

B. Data Understanding

The dataset belongs to the Public Nutrition Directorate (PND), Ministry of Public Health (MoPH), the Islamic Republic of Afghanistan. The data is a sample of the Afghanistan Nutrition SMART Survey from 2015 to 2018 from various administrative regions. The dataset contains 2,131 records includes birth date, visit date, age, sex, height, weight, province, age group, mid-upper arm circumference

(MUAC), and nutritional oedema features. The dependent variables were imbalanced, the majority class belonged to oedema which contained 85.57% (no) and only 14.43% (yes). Table V elaborates the distribution of malnutrition status in the dataset.

C. Data Preparation

This step was a crucial phase of our process, where we prepared data as input data for the models. The data preparation has consisted of two phases: anthropometric data analysis and preprocessing for data mining algorithms.

1) Anthropometric Data Analysis

Anthropometric indices are widely used to measure the intensity of malnutrition. WHO 2006 standard offers four significant indices: length/height-for-age, weight-for-height, weight-for-age, and BMI-for-age [28]. Based on the WHO's standard, three anthropometric indices Weight-for-Age Z-score (WAZ), Height-for-Age Z-score (HAZ), and Weight-for-Height Z-score (WHZ) calculated for each child. Calculation aimed to find the Z-score normalization for each child associated with his/her age, height, weight, and sex concerning the distribution of the standard reference population table for the same age, height, weight, and sex. Equation (1) defines the Z-score calculation based on the WHO's 2006 standard.

$$\text{Z-Score} = \frac{X-M}{\sigma} \tag{1}$$

Here, X refers to observed value (height), M refers to the median of WHO's reference population, and σ is the standard deviation of WHO's reference population. Equation (1) is suitable for normal distributions, and the height distribution is normal in the WHO's growth reference population. Thus, the height-for-age Z-score is calculated based on (1). In the WHO's child growth reference population, the weight has non-normal distribution. The weight-for-age and weight-for-height/length were calculated by (2).

$$\text{Z-Score} = \frac{(X \div M)^{L}-1}{L*S} \tag{2}$$

Where X is the observed value (weight), M refers to the median of WHO's reference population, L is the power needed to remove the skewness, and S is the coefficient of variation.

During the Z-score calculation, some values spanned out from the standard Z-score values. These values were recognized as out of range output based on the WHO's flagging system. Table I indicates the WHO's flagging system. In the dataset there were 1.4% flags (out of range values) for length or height-for-age, 1.6% for weight-for-age and 8.8% for weight-for-length or height.

After the out of range values were eliminated, the training dataset was refined with oedema, stunted, underweight, and wasted labels. Table II indicates the final dataset. The labels were assigned based on WHO's multicenter growth standard definitions for each indicator, reported in Table III. Moreover, two other essential definitions, MUAC and oedema, were also considered as these were existed in the dataset. MUAC and oedema both define wasted status. Oedema is a clinical sign. Table IV indicates the bilateral pitting nutritional oedema and MUAC definitions for malnutrition status. It is noteworthy that MUAC < 112mm is usually seen in infants less than 6 months. Thus, MUAC measurement is not yet used for a children less than 6 months. Based on literature, this indicator is not reliable for infants less than 6 months [16].

2) Preprocessing for Data Mining

In this phase, to fit the data on the models, the missing values were replaced with the mean value. Data was checked for outliers, the out of range values based on WHO's standard for transformed attributes considered as extreme values. The overweight status also removed because it was out of the scope of this study.

D. Data Mining

On the cleaned dataset, four well-known algorithms, namely Random Forest (RF), PART rule induction, Naïve Bayes (NB), and Logistic Regression (LR) were applied using the WEKA machine learning tool. The dataset was split into 80% training and 20% testing data. "Correlation Attribute Eval" method was used to evaluate the significance of attributes for each model. When building the models, two sets of features were evaluated and employed. The first set includes sex, age, weight, height, MUAC, province, and age group. The second set contained all these mentioned attributes with their associated transformed attributes. The transformed attributes were anthropometric indices HAZ, WAZ, and WHZ for stunted, underweight, and wasted, respectively. For oedema model, there were no transformed features because it is a clinical sign and is not physically measurable, like weight and height.

The dataset was imbalanced, where the classification categories were not approximately equally represented. Unbalanced data classes can influence model accuracy. We applied a standard technique called Synthetic Minority Oversampling Technique (SMOTE) to make the data classes almost balanced. SMOTE uses the combination of under-sampling of the majority class and oversampling of minority class techniques to balance the class [29].

TABLE I. WHO'S Z-SCORE FLAGGING SYSTEM

Index	Lower Z-score	Upper Z-score
Weight-for-age	< -6	> +5
Length/height-for-age	< -6	> +6
Weight-for-height	< -5	> +5
BMI-for-age	< -5	> +5

TABLE II. FINAL DATASET ATTRIBUTES

#	Feature	Description
1	Sex	Sex of child
2	Birthdate	Date of birth of child
3	Visit_date	Date of survey
4	Age	Age of child in month
5	Weight	Weight of child in Kg
6	Height	Height of child in cm
7	MUAC	Mid-Upper Arm Circumference
8	Age_group	Child age group, 5 distinct groups of age
9	WAZ	Weight-for-Age Z-Score
10	HAZ	Height-for-Age Z-Score
11	WHZ	Weight-for-Height Z-Score
12	Province	Region of the child
13	Stunted	Indicates whether a child is stunted or not
14	Underweight	Indicates if child is underweighted
15	Wasted	Indicates whether a child is wasted or not
16	Oedema	Bilateral pitting oedema in both feet

TABLE III. WHO'S MALNUTRITION DEFINITION BASED ON ANTHROPOMETRIC PARAMETERS.

Measurement	Classification
Weight-for-Age Z-Score	
Between -2 SD and 2 SD	Normal
From -2 SD to -3 SD or lower	Underweight
Height-for-Age Z-Score	
Between -2 SD and 2 SD	Normal
From -2 SD to -3 SD or lower	Stunted
Weight-for-Height Z-Score	
Between -2 SD and 2 SD	Normal
From -2 SD to -3 SD or lower	Wasted

TABLE IV. OEDEMA AND MUAC DEFINITION BASED ON WHO

Having Bilateral Pitting Oedema on both feet	
Yes	Wasted
No	Not Wasted
MUAC (Mid-Upper Arm Circumference)	
112 mm < MUAC < 125 mm	Wasted
MUAC > 125 mm	Not Wasted

TABLE V. DISTRIBUTION OF MALNUTRITION STATUS

Status	Yes	No
Oedema	14.43 %	85.57 %
Stunted	53.23 %	46.77 %
Underweight	28.96 %	71.04 %
Wasted	15.29 %	84.71 %

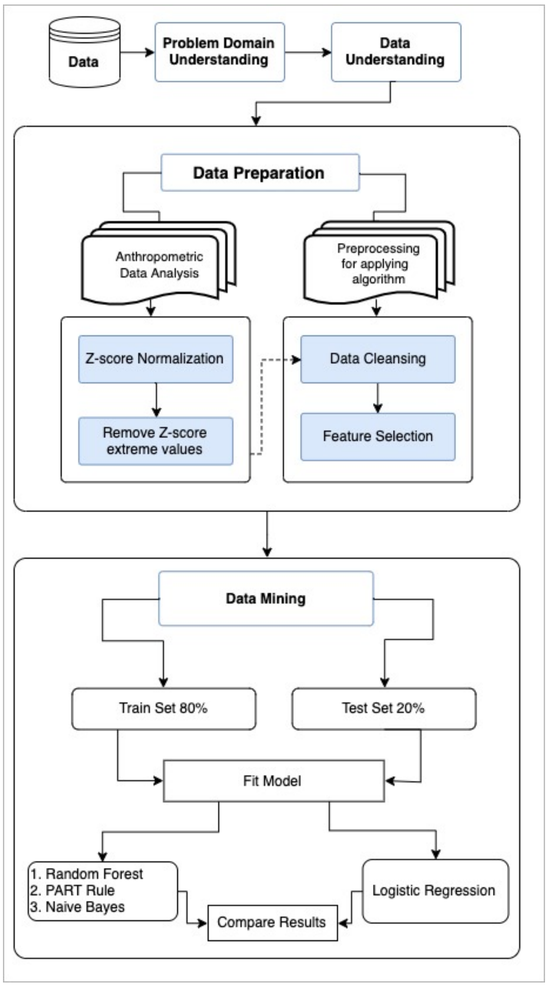

Fig. 1. Flow of proposed model.

V. RESULTS

In this section, we represent the experimental results. The study aimed to identify whether a child is in the stunted, wasted, underweight status of malnutrition, or has nutritional oedema. We built four different models using four data mining well-known algorithms, namely RF, PART, NB, and LR. All the experimentations during model building applied after SMOTE (300%) which are described as follows:

A. *Stunted*

Stunted, with its transformed attribute, gained 99.99%, 99.99%, and 95.82% accuracy for RF, PART, and NB, respectively. While, without a transformed feature, the obtained accuracy for RF, PART, and NB were 98.29%, 97.5%, and 75.47%, respectively. The LR with and without transformed feature obtained 98.89% and 95.53% accuracy respectively. Table VI illustrates the results for stunted status for both (with and without) transformed features.

B. *Wasted*

To predict the wasted status of the children, the model with a transformed attribute (WHZ) achieved 99.75%, 99.56%, 97.59%, and 91.89% accuracy for RF, PART, NB, and LR respectively. When the transformed feature was omitted, the model obtained 98.48%, 98.04%, 90.83%, and 92.02% accuracies for RF, PART, NB, and LR respectively. The details of the wasted model's results are represented in Table VII.

C. *Underweight*

The underweight model was also tested with and without its transformed feature (WAZ). The results obtained with its transformed attribute were 99.42%, 99.42%, 95.65%, and 98.87% for RF, PART, NB and, LR respectively. When the model experimented without its transformed attribute, the obtained accuracy was 97.83%, 96.09%, 80.50%, and 91.55% for RF, PART, NB, and LR respectively. Table VIII depicts the result details for underweight status.

D. *Oedema*

For the oedema model, there was no transformed feature. This model was only tested with the first set of attributes, as mentioned earlier. The empirical results for this model achieved the accuracy of 97.20%, 94.93%, 87.44%, and 88.35% for RF, PART, NB, and LR respectively. Table IX represents the details of the results for the oedema model.

TABLE VI. STUNTED MODEL EXPERIMENTAL RESULTS WITH AND WITHOUT TRANSFORMED FEATURE.

Stunted (Accuracy)			
Model	***SMOTE***	***With Transformed Attribute***	***Without Transformed Attribute***
RF	Before	99.71 %	92.95 %
	300 %	**99.99** %	98.29 %
PART	Before	99.71 %	91.83 %
	300 %	**99.99** %	97.5 %
NB	Before	95.39 %	65.07 %
	300 %	95.82 %	75.47 %
LR	Before	98.18%	95.39%
	300 %	98.89%	95.53%

TABLE VII. WASTED MODEL EXPERIMENTAL RESULTS WITH AND WITHOUT TRANSFORMED FEATURE.

Wasted (Accuracy)			
Model	***SMOTE***	***With Transformed Attribute***	***Without Transformed Attribute***
RF	Before	99.45 %	93.46 %
	300 %	**99.75 %**	98.48 %
PART	Before	99.55 %	94.27 %
	300 %	99.56 %	98.04 %
NB	Before	97.00 %	89.92 %
	300 %	97.59 %	90.83 %
LR	Before	76.15 %	87.77 %
	300 %	91.89 %	92.02 %

TABLE VIII. UNDERWEIGHT MODEL EXPERIMENTAL RESULTS WITH AND WITHOUT TRANSFORMED FEATURE.

Underweight (Accuracy)			
Model	***SMOTE***	***With Transformed Attribute***	***Without Transformed Attribute***
RF	Before	**99.72** %	94.58 %
	300 %	99.42 %	97.83 %
PART	Before	**99.72** %	93.77 %
	300 %	99.42 %	96.09 %
NB	Before	95.12 %	80.48 %
	300 %	95.65 %	80.50 %
LR	Before	98.45 %	87.53 %
	300%	98.87 %	91.55 %

TABLE IX. OEDEMA MODEL EXPERIMENTAL RESULTS.

Oedema		
Model	***SMOTE***	***Accuracy***
RF	Before	84.46 %
	300 %	**97.20** %
PART	Before	82.83 %
	300 %	94.93 %
NB	Before	83.10 %
	300 %	87.44 %
LR	Before	82.53 %
	300%	88.35 %

Generally, we can still state that the most striking results came from RF for both sets of attributes, and the result of PART was also much more alike to RF. The NB and LR performed poorly than RF and PART in both cases (with and without transformed features). We can say, PART and RF were suitable classification algorithms for predicting malnutrition status of preschool-age children for both nutritional oedema and anthropometric parameters.

VI. DISCUSSION

This study identifies the malnutrition status of preschool-age children through anthropometric parameters and clinical indicators. The experiments designed for three primary purposes; to investigate the effect of decision tree when generating the tree models, to examine how the feature selection affects the classification accuracy, and to compare all the four utilized techniques to determine which one is performing well with regards to malnutrition prediction.

Tables VI and VII in the results section, there is no more variation in the accuracy before and after applying SMOTE with transformed features. However, without transformed attributes, SMOTE expectedly enhanced the accuracy. In contradiction, underweight status with its transformed feature obtained high accuracy before SMOTE is applied, as indicated in Table VIII in the results section. However, applying SMOTE on underweight without a transformed feature provided good enough results. It was found that since the transformed features (HAZ, WAZ, and WHZ) were actually used to annotate the nutritional status, these features can directly define the malnutrition status. That is why their accuracy is much higher than the models without transformed features. However, the important aspect of this study is the prediction of nutritional oedema.

In stunted and wasted statuses, RF, PART, and NB performed better than the LR model in both cases (with and without transformed feature). In underweight and oedema statuses, LR obtained high accuracy than NB in both cases, but RF and PART accuracy was higher than LR. In general, RF and PART performed better, the reason may depend on structure of data. For this study, the training dataset was organized based on WHO's predefined rules and definitions for malnutrition status. Accordingly, trees can easily handle such kind of data and that is why they obtained the highest accuracy.

The oedema model was not examined with transformed features because from the domain area experts and literature perspectives, HAZ, WAZ, and WHZ are not perfect indicators for identifying nutritional oedema [16]. For this model, before the SMOTE operation, the result was not satisfactory due to imbalanced classes. When SMOTE (300%) was applied, the RF algorithm obtained high accuracy as shown in Table IX in the results section.

PART rule classifier generated IF-THEN rules for stunted, wasted, underweight, and oedema. Most of these rules were consistent with the rules supported by literature and domain area specialists [16, 30]. These rules can be applied to the real-world applications to identify malnutrition status, such as a decision support system for detecting and diagnosing malnourished children.

The major contribution of this study is the incorporation of clinical symptoms with anthropometric parameters and the prediction of nutritional oedema. While the clinical symptoms have not been used in other studies, another significance of this study is the use of data; other studies [17, 18, 19, 23, 21] employed public datasets, especially DHS. While this study incorporated a specific nutrition dataset that was collected through SMART methodology by the Ministry of Public Health of Afghanistan (MoPH), this can lead our results to be much more reliable.

The findings of this study reveal a positive association between the clinical symptoms and anthropometric parameters to define the malnutrition status in preschool-age children. The experimental results of this study confirm that data mining classification algorithms have an outstanding contribution in healthcare, particularly in identifying malnutrition status in preschool-age children not only through anthropometric parameters but also clinical symptoms and other diseases. Our model could be an alternative for other existing models in predicting or classifying malnutrition status. However, this study has shortcomings in that it does not include socioeconomic, cultural, household, maternal care variables, all of which reported as more important predictors in [23].

VII. CONCLUSION

Nowadays, data mining is more prevalent in many research areas. In healthcare, it is applied for various purposes such as identifying diabetes, influenza, and cancer. However, the potential of data mining has not yet been utilized to classify the malnutrition status of preschool-age children in

Afghanistan. This study proposed an alternative approach to predict the malnutrition status of the Afghan children using Afghanistan Nutrition SMART survey data. In our exploration, four separate models have been created for each status using RF, PART, NB, and LR.

For future work, in addition to using the anthropometric parameters along with limited clinical symptoms of children to predict malnutrition status, we could use other features such as socioeconomic, maternal care for child, cultural characteristics, and other clinical symptoms of the Afghan children to have more complete results. In order to commence utilizing the models for practical decision-making, we will deploy the models into a real production, this could be a web application for malnutrition detection and monitoring of pre-school age children.

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