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Monitoring The Children's Health Status and Forecasting Height with Nutritional Advice

Kim Ngan Nguyen*, Nu Hoang Vi Ton*, Tran Minh Khuong Vu**, Pham The Bao**★

Abstract

Children's health is interesting to parents and society. A system that assists to monitor the development of their children and gives nutritional advices is an interesting of parents. In this study, we present a system that allows to track the heights and weights of a child since he/she was born up to adulthood, to predict his age of puberty, and to provide nutritional advice. Particularly, it predicts the height in near future and the adult stature for detecting the child with abnormal development. We applied Sager's model for predicting the height in near future by using interpolation and regression techniques before puberty. After determining the puberty time, we proposed a model for predicting the height. Then we applied fuzzy logic for evaluating the health status and providing nutritional advice. Our system predicted stature in near future with error bound of 1.7361±0.0397 cm in girls and 2.4020±0.0799 cm in boys. Our model also gave a reliable adult stature prediction with error bound of 0.3507±0.2808 cm in girls and 1.3414±0.7024 cm in boys. At the same time, the nutrition was provided appropriately in terms of protein, lipid, glucid. We implemented a program based on this research. Our system promises to improve the health of every child.

Key words : Fuzzy logic, Height prediction, child development, time of puberty, nutrition advice

Ⅰ. Introduction

Accurate predictions of height and weight are of considerable interests to pediatricians, children, and their parents because they are often used in evaluation of a child's growth. These predictions are important for detecting children with developmental problems. A reliable predictor helps pediatricians adjust the nutrition supplements which enhance the children's development.

In this study, we proposed an approach to construct a system that helps parents monitor the children's development in heights and weights. In the past, from the inputs including gender, age (in months), heights (in centimeters) and weights (in kilograms), our system can predict the heights of the child in next three or twelve months. At the same time, the system evaluates his health status and then suggests an appropriated nutritional advice. The system can even notify the parents when the child reaches puberty and then predict his adult stature.

For recent years, predicting the adult stature of the children has been attracted considerable attention from researchers. A simple approach is using simple formulas such as Mid-Parent Rule.

* Faculty of Mathematics and Applications, Sai Gon University, Vietnam
** Math and Computer Science Faculty, Ho Chi Minh University of Science, Vietnam
★ Corresponding author
E-mail : ptbao2005@gmail.com, Tel : +84-28-3835-0098
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This rule constructs a simple formula based on the heights of the parents and the child's gender. It supposed that child's adult height is somewhere between their mother's and father's heights [14]. More sophisticatedly, there are methods using more information such as gender characteristics [1] [2], or anthropometry [3] [4] [17], etc. Methods based on this approach do not give a reliable result.

Modern approaches give more accurate results are based on biological information such as bone age [5] [6] or genome [7]. However, these methods require modern equipments and highly skilled person. Therefore, only pediatricians and endocrinologists can use these procedures effectively. In fact, the applicability of these approaches is limited.

Another approach is using mathematical methods. Sherar et al. [8] proposed a simple method using maturity and gender-specific cumulative height velocity curves. It is reported that this method can predict adult height within 5.35 cm 95% of the time in boys and 6.81 cm 95% of the time in girls.

Sager [9] proposed a mathematical model to monitor the development in height of children. He found that the height of a child up to puberty can be approximated by a power function, formula (1).

$$pw = h_0 + kt^l \tag{1}$$

where t is age, h_0 is the height (length) at birth, k and l are parameters. However, this formula is no longer true during and after puberty.

Our primary objective is to predict the heights in near future and the adult height of a child. We used a quartic polynomial to predict height of a child after reaching puberty. Moreover, from that function, we notify the parents when the child reaches puberty and predict the adult height. Besides, we used body mass index (BMI) and fuzzy system to diagnose the health status [19] [20] [21].

II. Methods and materials

1. Subjects

The dataset was provided publicly on http://www.cdc.gov/growthcharts/zscore.htm. It consisted of weight-for-age and height-for-age values corresponding to specific z-scores (-2, -1.5, -1, -0.5, 0, 0.5, 1, 1.5, 2). These values were provided by age (up to 20 years old) and gender [15] [16]. Table 1 is a sample of a boy's data corresponding to $z-scores=0$.

Table 1. Height-and weight-for-age of a boy of $z-scores=0$.

Gender	Age months	Height (cm)	Weight (kg)
1	0	49.98888	3.530203
1	1	54.6622	4.441316
1	2	58.11869	5.276207
1	3	60.84298	6.03214
1	4	63.14693	6.716614
1	5	65.17109	7.336131
1	6	66.99275	7.896688
1	7	68.65963	8.403892
1	8	70.20356	8.862976
1	9	71.64695	9.27881
1	10	73.00626	9.655904
…	…	…	…
1	24	86.4522	12.67076
1	25	87.25263	12.81159
1	26	88.03234	12.94993
1	27	88.79294	13.08658
1	28	89.53577	13.22224
1	29	90.26194	13.35753
1	30	90.97243	13.49296
1	31	91.66808	13.62901
1	32	92.34966	13.76605
1	33	93.01791	13.90441
1	34	93.67352	14.04438
1	35	94.31719	14.18616
1	36	94.94963	14.32994
…	…	…	…
1	108	133.5118	28.55056
1	109	133.9562	28.81288
1	110	134.3967	29.07857
1	111	134.8334	29.34771
1	112	135.2666	29.62035
1	113	135.6962	29.89656
1	114	136.1224	30.1764

Gender	Age months	Height (cm)	Weight (kg)
1	115	136.5454	30.45994
1	116	136.9653	30.74723
1	117	137.3824	31.03833
1	118	137.7969	31.3333
1	119	138.209	31.63219
1	120	138.6191	31.93505
...	...	...	...
1	228	176.6047	69.12351
1	229	176.6307	69.26527
1	230	176.6556	69.4047
1	231	176.6793	69.54171
1	232	176.7018	69.67613
1	233	176.7234	69.80767
1	234	176.7439	69.93594
1	235	176.7635	70.06042
1	236	176.7822	70.18047
1	237	176.8001	70.29527
1	238	176.8172	70.40385
1	239	176.8336	70.50508
1	240	176.8492	70.59761

2. Monitoring the growth development

First of all, our system required that users should input the data monthly. However, in real application, because of some reasons, the data was not always provided frequently and adequately. To overcome this problem, we used spline interpolation to fill in the missing data. Spline interpolation is a popular technique in mathematics which is used for finding values within the range of a given dataset.

Cubic spline interpolation is the most popular technique because of its simplicity and stability. The spline interpolation is based on the following principle. The interpolation interval is divided into small subintervals. Each of these subintervals is interpolated by using a third-degree polynomial. Intermediate values of the independent variable can be approximated by values of these functions.

In this study, we used cubic spline interpolation to obtain the heights and weights at intermediate age values.

3. Height prediction before puberty

In order to construct model expressed in (1) for a specific child, we estimated the parameters by means of linear regression technique. This technique is also common in mathematics. It automatically tries to explore the correlation among variables. Therefore, it is able to predict values of data points which are out of range of the dataset. In fact, regression is widely used for prediction.

For example, given a dataset of age months (t) and heights (h) (t_1, h_1), (t_2, h_2),... (t_n, h_n), we assume that the relationship between t and h is (2).

$$\hat{h} = f(t) = at + b \tag{2}$$

where a and b are parameters.

Linear regression finds values of a and b that minimize the sum of squared errors (3).

$$SSE = \sum_{i=1}^{N} (f(t_i) - h_i)^2 \tag{3}$$

By means of partial derivatives with respect to a and b, we obtained the following formulas (4) and (5).

$$a = \frac{n\sum h_i t_i - \sum t_i \sum h_i}{n\sum t_i^2 - (\sum t_i)^2} \tag{4}$$

$$b = \frac{\sum t_i^2 \sum h_i - \sum t_i \sum t_i h_i}{n\sum t_i^2 - (\sum t_i)^2} \tag{5}$$

In order to apply linear regression method, we transformed the model (1) to (6)

$$\ln(pw - h_0) = \ln(k) + l\ln(t) \tag{6}$$

Then we used linear regression for estimating the values of $\ln(k)$ and l.

Algorithm 1 : Constructing the height prediction model
Input: heights $h = (h_0, h_1, h_2, \cdots, h_n)$ for age months $t = (t_0, t_1, t_2, ..., t_n)$
Output: estimated parameters of model (1)
Step 1: For all $i = 0, 1, ... n$

$$h_i' = \ln(h_i - h_0) \qquad (1.1)$$

Step 2: Using the formulas (4) and (5) to obtain the estimated values of linear regression parameters a and b.
Step 3: The model parameters are

$$l = a \qquad (1.2)$$
$$k = e^b \qquad (1.2)$$

After obtaining the prediction model, we apply it to predict the heights in next three months and twelve months.

4. Height prediction after reaching puberty

As stated above, we constructed a quartic polynomial, g, for predicting heights after reaching puberty. From figure 1, we saw that in puberty period, rate of growth in height getsits local minimum at the start of puberty, t_M, and reaches its local maximum aroundtwo years later, t_M. Then the growth rate decrease to zerowhen the puberty finishes, $t_{\max}$. In addition, the function has a doubleroot at $t_{\max}$.

Hence, we constructed a quartic function whose form is given by (7).

$$g(t) = a(t - t_{\max})^4 + b(t - t_{\max})^3 + c(t - t_{\max})^2 \qquad (7)$$

where a, b, c are parameters and $t_{\max}$ is the unknown constant.

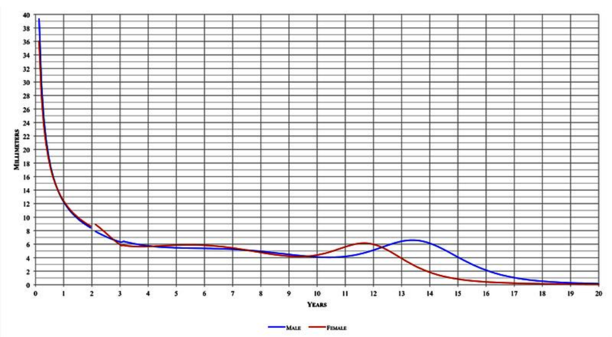

Figure 1. Human height growth per month, United States (50th percentile), source: Centers for Disease Control and Prevention.

In order to determine the function g, we fitted it and its first derivative to first and second derivative of pw at a time near t_m, t_1.

$$g(t_1) = pw'(t_1) \qquad (8)$$

$$g'(t_1) = pw''(t_1) \qquad (9)$$

r_m and r_M are ratio of growth rate at t_m and t_M to t_1 respectively.

$$g(t_m) = r_m pw'(t_1) \qquad (10)$$

$$g(t_M) = r_M pw'(t_1) \qquad (11)$$

t_m is local minimum and t_M is local maximum of g, formula (12) and (13).

$$g'(t_m) = 0 \qquad (12)$$

$$g'(t_M) = 0 \qquad (13)$$

After solving equations (8) (9) (10) (11) (12) (13), we obtained values of coefficientsof g as well as r_m, r_M and $t_{\max}$.

The adult stature was given by (14).

$$h_{\max} = pw(t_1) - h_g(t_1) \qquad (14)$$

where h_g is the antiderivative of function g.

Finally, we obtained the height prediction model in the puberty period.

$$h(t) = h_g(t) + h_{\max} \qquad (15)$$

Before t_M, we estimated this value around two year after t_m.

5. Predicting puberty

As stated above, rate of growth in height gets its local minimum at the start of puberty, t_m, and then reaches its local maximum at t_M. Hence, weutilized the growth rate to predict the time of beginning puberty. The basic idea is considering the tangent vector of the height function at each month and evaluating its characteristics.

Algorithm 2: Predicting puberty
Input: height vector $h = (h_0, h_1, h_2, \ldots, h_n)$ and age vector $m = (m_0, m_1, m_2, \ldots, m_n)$ where $m_0 < m_1 < \cdots < m_n$
Output: the starting time of puberty, t_m, and the time where growth reach its peak, t_M.

Step 1: From the given data, interpolate the height function $f(x)$.
Step 2: For all $j = 1, 2, \ldots n$:

$$\overrightarrow{u_j} = \left(1, \frac{f(m_j) - f(m_{j-1})}{m_j - m_{j-1}}\right) \qquad (2.1)$$

$$\alpha_j = \arccos\left(\frac{\overrightarrow{u_j} \cdot \vec{i}}{|\overrightarrow{u_j}|\ |\vec{i}|}\right) \quad (2.2)$$

where $\vec{i} = (1,0)$

Step 4: If there exists k such that

$$\begin{cases} k = \arg\min_j \{\alpha_j\} \\ \alpha_{k+1} \geq \alpha_k \end{cases} \quad (2.3)$$

$t_m = k$ and go to step 5

Else

$t_m = \text{none}$

Terminate the algorithm

Step 5: If there exists $l$such that

$$\begin{cases} l = \arg\max_j \{\alpha_j\} \\ \alpha_{l+1} \leq \alpha_l \end{cases} \quad (2.4)$$

Return $t_M = l$

Else

$t_M = \text{none}$

Terminate the algorithm and notify that was not reaching "t_M"

6. Providing nutrition advice

In this work, we used fuzzy logic to evaluate the health status then we suggest the nutrient amount by using Mamdani inference method. The fuzzy method consists of four processes: fuzzification, rule base, fuzzy inference[18][22], defuzzification (figure 2). These processes featured in linguistic variables whose values are words. We constructed one input variables, HS, for evaluating the child's health status and three output variables(r_P, r_G, r_L) for providing the nutrient ratio.

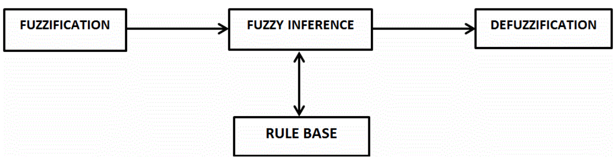

Figure 2. Fuzzy system model.

Human body requires amount of energy to function regularly. This energy is known as the basal metabolic rate (BMR). The Mifflin St. Jeor equation is a standard formula for calculating BMR[10].

$$\mathrm{BMR}(w,h,a,g) = 10 \times w + 6.25 \times h - 5 \times a + r_0(g) \quad (16)$$

where w is weight (in kg), h is height (in cm), a is age (in years), g is gender and

$$r_0(g) = \begin{cases} 5, & g = \text{male} \\ -161, & g = \text{female} \end{cases} \quad (17)$$

The energy is provided mainly through three macronutrient groups: protein (P), glucid (G), lipid (L). Hence, we calculated the amount of protein, glucid, lipid from the amount of energy.

However, the nutrition need is varied by health status. For example, an obese child needslipid less than a normal child. According to World Health Organization (WHO), the health statuswas categorized into nine classes: third-degree malnutrition, second-degree malnutrition, first-degree malnutrition, underweight, normal, overweight, first-degree obesity, second-degree obesity, third-degree obesity. In fact, BMI is a well-known indicator for evaluating the health status and accepted by WHO[11].

$$\mathrm{BMI} = \frac{\text{weight}}{\text{height}^2} \quad (18)$$

Malnutrition is a condition that results from a diet which is insufficient of essential nutrients. WHO categorized the malnutrition into three degrees based on the percentage of median body weight for age and gender: first-degree involves a weight of 70-80% of median body weight; second-degree involves a weight of 60-70% of median body weight, third-degree involves a weight of less than 60% of median body weight.

Obesity is the condition of excess of nutrients. Several degrees of obesity are distinguished: first-degree obesity involves a 29% weight increase above median body weight; second-degree involves a 30-49% increase above median body weight; third-degree involves a 50-99% increase above median body weight.

In the fuzzification process, we establishednine linguistic values of HS corresponding to nine health status indicators:third-degree malnutrition, second-degree malnutrition, first-degree malnutrition, underweight, normal, overweight, first-degree obesity, second-degree obesity, third-degree obesity. The membership function for each variable considers the information of BMI.

The membership function θ for each linguistic value was a triangular-shaped function with three parameters T_1, T_2, T_3. We selected the triangular-shaped function because it is the most popular one. Figure 3 illustrates the behavior of the triangular-shaped function. These parameters were established based on WHO 2006.

$$\theta(\mathrm{F}) = \begin{cases} 0, & \mathrm{F} < T_1 \\ \dfrac{\mathrm{F} - T_1}{T_2 - T_1}, & T_1 \leq \mathrm{F} < T_2 \\ \dfrac{T_3 - \mathrm{F}}{T_3 - T_2}, & T_2 \leq \mathrm{F} < T_3 \\ 0, & \mathrm{F} \geq T_3 \end{cases} \tag{19}$$

Similarly, for each output variable, we also established nine linguistic values corresponding to nine energy requirements for nine health statuses. The membership functions of these variables consider the ratio P:G:L for health statuses. The parameters were given in table 3.

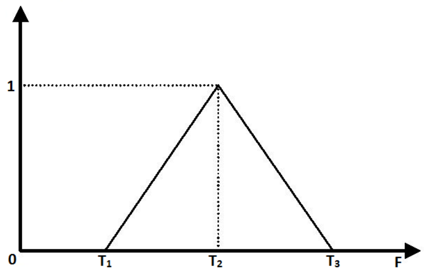

Figure 3. Triangular-shaped function.

Algorithm 3: Evaluating health status Input: age (m), weight (w), height (h), gender (g) Output: health status of the child Step 1: Selecting the fuzzy system corresponding to the age and the gender Step 2: Calculating the membership degrees of HS Step 3: The HS takes on the value whose membership degree is highest

The rule base is a collection of “If … then …” rules. These rules utilized linguistic variables we constructed before. Table 2 presents the rule base we used.

Table 2. The fuzzy rule base in our system.

If HS is first-degree malnutrition	Then is first-degree malnutrition
If HS is second-degree malnutrition	Then is second-degree malnutrition
If HS is first-degree malnutrition	Then is third-degree malnutrition
If HS is underweight	Then is underweight
If HS is normal	Then is normal
If HS is overweight	Then is overweight
If HS is first-degree obesity	Then is first-degree obesity
If HS is second-degree obesity	Then is second-degree obesity
If HS is second-degree obesity	Then is third-degree obesity

Table 3. The parameters of each output variables.

Health status	$r_P(\%)$			$r_G(\%)$			$r_L(\%)$		
	T_1	T_2	T_3	T_1	T_2	T_3	T_1	T_2	T_3
Third-degree malnutrition	20	25	30	45	50	55	20	25	30
Second-degree malnutrition	15	20	25	50	55	60	20	25	30
First-degree malnutrition	15	20	25	45	50	55	25	30	35
Underweight	20	15	15	55	60	65	20	25	30
Normal	10	15	20	50	55	60	25	30	35
Overweight	15	20	25	55	60	65	15	20	25
First-degree obesity	20	25	30	60	65	70	10	15	20
Second-degree obesity	25	30	35	55	60	65	5	10	15
Third-degree obesity	30	35	40	60	65	70	5	10	15

From the rule base above, we applied Mamdani's inference method [12] to map the input (HS) to the outputs. This process provided fuzzy output values from which the defuzzification could provide the ration of nutrients.

In the defuzzification process, we provided the energy requirement according to the health status. From the fuzzy value obtained from fuzzy inference process, if the health status is malnutrition, we used middle of maximum (MOM) defuzzification method to obtain a quantifiable value. It is noted that normalization is necessary because the summation of these values might not be 100.

Algorithm 4: Calculating nutrients ratio according to the health status
Input: age (m), weight (w), height (h), gender (g)
Output: the ratio of nutrients r_P, r_G, r_L

Step 1: Evaluating the health status by using Algorithm 3
Step 2: Applying Mamdani's method and rule base to obtain the fuzzy values of output variables
Step 3: Applying the MOMdefuzzification method to obtain the r'_P, r'_G, r'_L
Step 4: Normalize these ratio

$$r_P = \frac{r'_P}{r'_P + r'_G + r'_L} \quad r_G = \frac{r'_G}{r'_P + r'_G + r'_L} \quad r_L = \frac{r'_L}{r'_P + r'_G + r'_L}$$

Algorithm 5: Providing nutritional advice
Input: age (m), weight (w), height (h), gender (g)
Output: the amount of P, G, L in grams

Step 1: Selecting the fuzzy system corresponding to the age and the gender
Step 2: Evaluating the health status of the child (Algorithm 3) and calculating the nutrients ratio by using the selected system (Algorithm 4)
Step 3: Calculating the nutrient requirement in terms of P, G, L (in kcal)

$P = E \times r_P$ $\quad G = E \times r_G$ $\quad L = E \times r_L$

Step 4: Calculating the nutrient requirement in terms of P, G, L (in grams)

Pg=P/4 Gg=G/4 Lg=L/9;

We produced 228 fuzzy systems for boys and 228 fuzzy systems for girls to suggest the required energy in kcal from 1 to 228 months. Then we calculated the amount of protein, glucid, lipid based on that energy.

III. Result

1. Interface

We used MATLAB to implement our method. Figure 4 is the main interface of our application. Before importing a new data, our system validates it for ensuring that the information is clean, feasible and useful. Unsatisfied data can be one of following cases:

- The age month was already existed.
- The height was lower than the previous one.
- The increase of height and weight exceed a threshold.

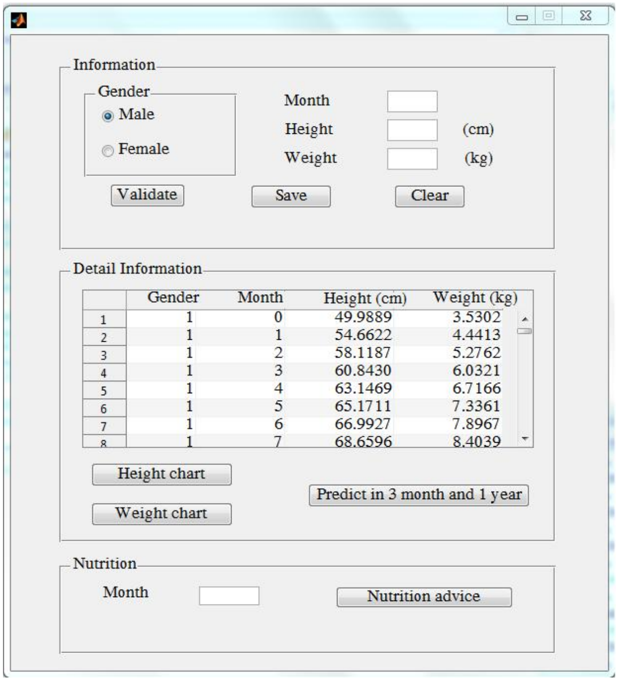

Figure 4. The main interface of our system.

After validating the data, the satisfied data will be imported and displayed in "Detail Information" frame.

2. Monitoring the growth development

If users press "Height chart" button, our application displays the height chart for monitoring the development of the child (figure 5).

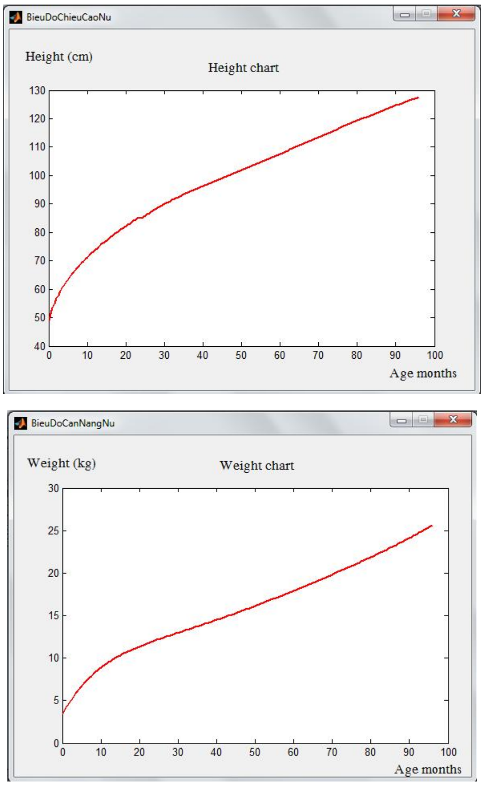

Figure 5. Height chart (left) and Weight chart (right).

3. Providing nutrition advice

From the current data, we used fuzzy system for evaluating the health status of child, then we provided nutrition advices according to the health status (figure 5).

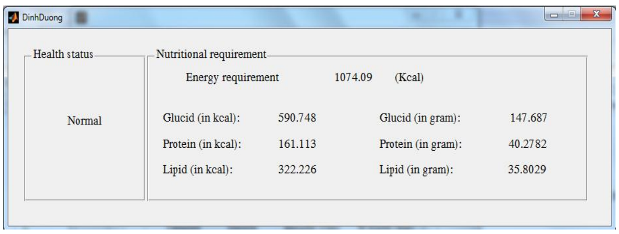

Figure 6. Nutrition advice.

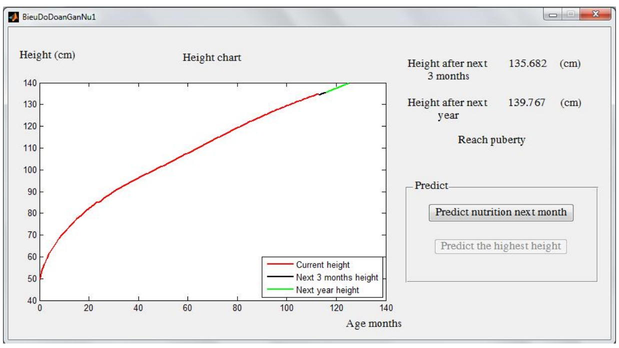

Figure 7. Predicting height during puberty.

4. Predicting puberty

Our program notifies the users when the child reaches his puberty (figure 7). This notification helps parents know that the child is in important period. We also notify when the growth rate reaches its peak.

Predicting the heights in next three months and twelve months before puberty

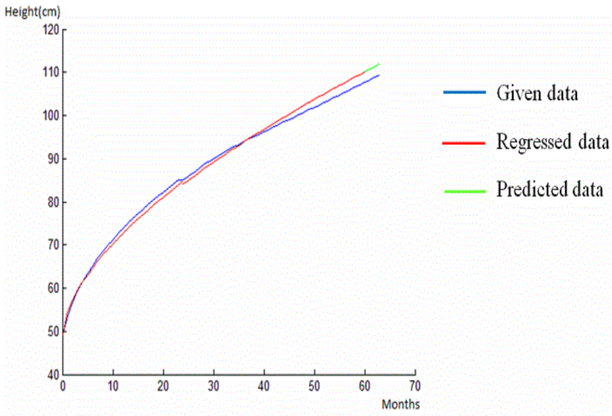

Figure 8. Predicting stature in next three months before puberty of a girl with z-score = 0 at 5 years old.

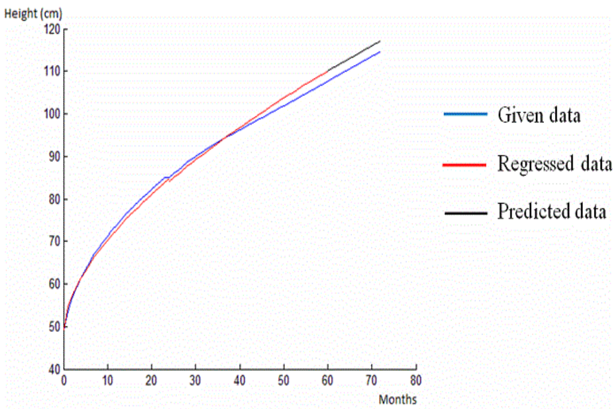

Figure 9. Predicting stature in next twelve months before puberty of a girl with z-score = 0 at 5 years old.

We predicted the height in near future from two years old up to puberty. For each month, we calculated the difference between given data and predicted data, then we reported the error bound. Figure 8 and 9 illustrate our prediction result. The error bounds of height prediction of a girl with z-score = 0 were given in table 4 and plotted in figure 10 and 11.

Table 4. Error bound for predicting from two years to puberty of a girl with z-score = 0.

Month	Error bound in next 3 months	Error bound in next 12 months
24	1.9254	4.0874
25	1.9182	4.1575
26	1.9326	4.2345
27	1.9671	4.3145
28	2.0209	4.3941
29	2.0925	4.4702
30	2.1803	4.5402
31	2.2825	4.6017
32	2.3971	4.6529
33	2.5219	4.6922
34	2.6322	4.7183
35	2.7326	4.7302
36	2.8220	4.7273
...	...	...
60	2.4562	2.4821
61	2.3774	2.3868
62	2.2970	2.2983
63	2.2156	2.2156
64	2.1395	2.1395
65	2.0656	2.0656
66	1.9908	1.9908
67	1.9153	1.9153
68	1.8396	1.8396
69	1.7638	1.7638
70	1.6885	1.6885
71	1.6139	1.6139
72	1.5402	1.5402
...	...	...
108	0.9252	1.1679
109	0.9494	1.1499
110	0.9714	1.1316
111	0.9904	1.1132
112	1.0057	1.0946
113	1.0167	1.0760
114	1.0226	1.0573
115	1.0226	1.0387
116	1.0160	1.0203
117	1.0021	1.0021
118	0.9842	0.9842
119	0.9667	0.9667
120	0.9452	0.9452
...	...	...
132	0.4483	2.1931
133	0.6264	2.3709
134	0.8100	2.5354
135	0.9971	2.6846
136	1.1859	2.8167
137	1.3743	2.9301
138	1.5600	3.0236
139	1.7410	3.0960
140	1.9151	3.1467
141	2.0799	3.1751
142	2.2337	3.1809
143	2.3743	3.1642
144	2.5000	3.1328
...	...	...
168	2.6500	2.6500
169	2.5655	2.5655
170	2.4633	2.4633
171	2.3443	2.3443
172	2.2092	2.2092
173	2.0590	2.0590
174	1.8948	1.8948
175	1.7175	1.7175
176	1.5281	1.5281
177	1.3275	1.3397
178	1.1168	1.6439
179	0.8968	1.9503
180	0.6684	2.2583

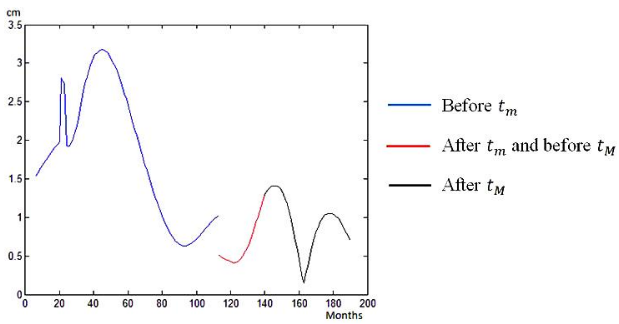

Figure 10. Error bound for predictions in next 3 months of a girl with z-score = 0.

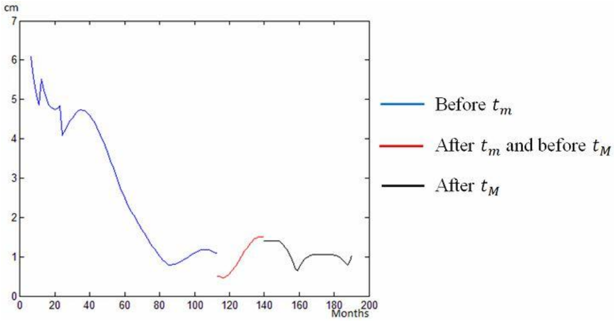

Figure 11. Error bound for predictions in next 12 months of a girl with z-score = 0.

Predicting the heights in next three months and twelve months after reaching puberty

When the child reaches puberty, we reported the error bound up to adulthood. We also predicted the adult stature (table 5 and 6). Figure 12 illustrates our result.

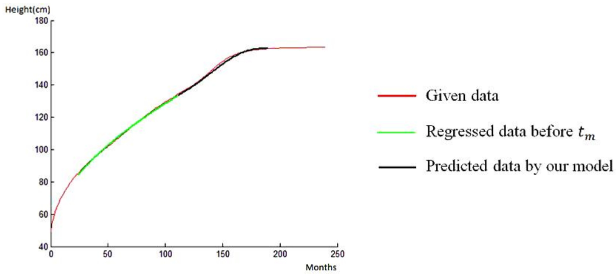

Figure 12. Predicting stature after reaching puberty of a girl with z-score = 0 at 12 years old.

Table 5. Error bound for predicting stature after reaching puberty and adult stature of girls.

No.	Error bound of model (7)		Predicting adult stature		
	3 months(Mean±SD)	12 months(Mean±SD)	Predicted stature	Adult stature	Error
1	0.9303±0.4927	1.2437±0.4419	151.2821	150.3327	0.9494
2	0.7333±0.5019	0.9939±0.5074	153.6376	153.5951	0.0425
3	0.8315±0.4747	1.1018±0.4354	157.0707	156.8500	0.2206
4	0.7526±0.4742	0.9483±0.4927	159.5965	160.0977	0.5012
5	0.8417±0.3501	1.0442±0.2985	163.2548	163.3383	0.0835
6	0.8562±0.3351	1.0373±0.2637	166.3672	166.5719	0.2047
7	0.7113±0.2634	0.8385±0.2006	169.2488	169.7987	0.5500
8	0.8529±0.5043	1.0411±0.5123	173.3389	173.0190	0.3199
9	0.7815±0.6647	0.9864±0.6942	176.5170	176.2328	0.2843

Table 6. Error bound for predicting stature after reaching puberty and adult stature of boys.

No.	Error bound of model (7)		Predicting adult stature		
	3 months(Mean±SD)	12 months(Mean±SD)	Predicted stature	Adult stature	Error
1	0.9578±0.7794	1.2071±0.7612	163.7352	162.4705	1.2647
2	0.6083±0.2688	0.7709±0.3456	165.8501	166.0845	0.2344
3	0.7111±0.4915	0.8777±0.5655	169.0368	169.6854	0.6486
4	1.3807±0.6353	1.6153±0.6158	171.3447	173.2735	1.9288
5	1.2101±0.7713	1.4296±0.7814	175.7508	176.8492	1.0984
6	1.3947±0.7617	1.6099±0.7484	179.0073	180.4129	1.4056
7	1.5467±0.7361	1.7535±0.6992	182.2702	183.9649	1.6947
8	1.2462±0.7943	1.4064±0.7649	186.3417	187.5054	1.1637
9	1.7679±0.5353	1.9429±0.4588	188.4009	191.0348	2.6339

IV. Conclusion

Our system predicted stature with error bound of 1.7361±0.0397 cm in girls and 2.4020±0.0799 cm in boys. The error statistics was given in table 7 and 8. The system gave a high accuracy prediction after the child reached four years old because then the data size is large enough for the regression model.

We proposed a model for predicting stature after reaching puberty. The result showed that our model gave a high accuracy predictor (table 5 and 6). At the same time, this model also gave a reliable adult stature prediction with error bound of 0.3507±0.2808 cm in girls and 1.3414±0.7024 cm in boys.

Table 7. The error statistics of predicting stature in girls.

No.	Error bound of predicting next 3 months			Error bound of predicting next 12 months		
	Mean	Max	Min	Mean	Max	Min
1	1.7454	3.5847	0.6301	2.3554	4.1704	0.7216
2	1.7340	3.4890	0.5857	2.3829	4.3355	0.7007
3	1.7169	3.2896	0.2797	2.3996	4.4795	0.7256
4	1.7235	3.0553	0.2942	2.4010	4.6078	0.7655
5	1.7349	3.1322	0.4483	2.3853	4.7273	0.8252
6	1.7298	3.2114	0.4760	2.3589	4.8473	0.9241
7	1.7119	3.3013	0.3630	2.3318	4.9801	1.0967
8	1.6942	3.4132	0.1814	2.3973	5.1433	1.2143
9	1.8341	3.5635	0.5163	2.6058	5.3620	0.5163

Another advantage of our system is the puberty notification. Because children in this period need an appropriated nutrition and a gymnastics fitness program for maximizing their stature, this notification is helpful for their parents.

Table 8. The error statistics of predicting stature in boys.

No.	Error bound of predicting next 3 months			Error bound of predicting next 12 months		
	Mean	Max	Min	Mean	Max	Min
1	1.0418	2.0666	0.1785	1.4367	3.1812	0.2063
2	1.0354	2.1522	0.0330	1.4728	3.5393	0.0611
3	1.1006	2.2471	0.0565	1.5333	3.8434	0.0631
4	1.1856	2.3791	0.0643	1.6476	4.0830	0.1587
5	1.2422	2.5022	0.1132	1.7287	4.2475	0.1797
6	1.2531	2.5814	0.0486	1.7705	4.3273	0.1160
7	1.2546	2.6117	0.0295	1.7888	4.3147	0.0512
8	1.2948	2.6615	0.0984	1.8528	4.1997	0.2197
9	1.3731	2.6983	0.2601	1.9582	4.0861	0.5429

Our method for providing nutrition advice is applicable to children without pathologic conditions such as diabetes, heart failure, etc. The nutrition was provided in terms of protein, lipid, glucid groups. We are considering of providing specific types from these groups for abnormal children.

In the future, we will provide suggestion on number of meals in day and menu for each meal. Moreover, nutrition for people with a specific pathology is a considerable trend. Beside, a gymnastics fitness program is a new improvement. Developing this application in mobile environment makes this system more friendly and applicable.

We have built an application on Android System for users with the name is ChildcareHelper [13] at Goole Play.

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BIOGRAPHY

Kim Ngan Nguyen (Member)

2015 : Bachelor Degree at Sai Gon University in Mathematics Applied.
2015~2018 : working as Software Engineer at Robert Bosch Engineering and Business Solution Limited Vietnam.
Research interests : software technologies, intelligent algorithm, block chain topics.

Nu Hoang Vi Ton (Member)

2015 : Bachelor Degree at Sai Gon University in Mathematics Applied.
2015~2018 : working as Software Engineer at Lac Viet Computing Corporation.
Research interests : software technologies, intelligent algorithm.

Tran Minh Khuong Vu (Member)

2014 : BS. degree in Ho Chi Minh City University of Science.
2018 : MSc. degree in Tokyo University of Agriculture and Technology.
2018 : Ph.D. student in Tokyo University of Agriculture and Technology.
Research interests : Image processing, Handwriting recognition, Machine Learning, User Interface

Pham The Bao (Member)

1995 : BS., 2000 : MSc., 2009: Ph.D. degrees in University of Science.
1995~2018 : Lecturer in the Department Computer Science, Faculty of Mathematics & Computer Science, University of Science, Hochiminh city, Vietnam.
Research interests : Image processing & pattern recognition, intelligent computing