The Development of Obesity Forecasting Model using Fuzzy Data Mining Techniques: Case study of the Primary School in Lower Northern Provinces (Thailand)

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Abstract

In general, obesity is calculated using the BMI, which is found to have limitations of use when we insert only one type of non-quantitative data as a crisp value, which is commonly used, or even create an obesity forecasting model using data mining techniques. If there is an input of weight and height data as a forecasting factor in various types of data, such as crisp value, estimated value and Fuzzy Linguistic Term value, etc. The algorithm will not possibly work under the data mining technique with such input data.

This research presented the solution for this problem in order to enable data mining techniques under limitations of inserted data, including crisp value, estimated value and fuzzy linguistic term value, for forecasting obesity. The researchers created a fuzzy database system in the form of Conceptual Meta Schema to support fuzzy attributed data storage. In addition, there were 3 types of fuzzy attribute matching as follows; Type 1 was matching crisp value with fuzzy linguistic term value, Type 2 was matching estimated value with fuzzy linguistic term value, and Type 3 was matching fuzzy linguistic term value with fuzzy linguistic term value, respectively. The attribute node from these fuzzy attributes would be selected to be used in the work of data mining techniques. Therefore, in this research, the researchers presented and compared the fuzzy model of working under the algorithm of data mining techniques in the form called fuzzy neural network and fuzzy decision tree techniques. The research result, it was found that the appropriate models for predicting obesity were fuzzy neural network algorithm with the neural network structure being 31-3-3, momentum at 0.2, learning rate at 0.3, under dividing data to test with cross-validation folds = 10 yielded accuracy value, precision value, recall value and f-measure at 84.3%, 82.7%, 84.3%, and 82.8%, respectively.

Keywords: Obesity, Fuzzy Neural Net, Fuzzy Decision Tree, Fuzzy Attribute Matching, Forecasting Model

Introduction

Obesity is a health problem which is almost found in every country. The World Health Organization estimated that up to 700 million people of the world's population will suffer from obesity in 2015. According to Statistical Thai Health Status Report , in Thailand, it was found that obesity in primary school children aged 6-12 years has increased rapidly. The factors of childhood obesity in the children could be identified in details as both quantitative and qualitative factors, divided into 3 sections, including children personal behavior section, social and family surrounding section and inside and outside school area environment section. However, to be identified having obesity, there is a widely used principle for evaluation, which is calculation with BMI. Still, different countries have different calculation and value of BMI (Ioannis et al., 2012; Michael, Carolyn, Claudia, & Luciano, 2004). Thus, using BMI as a measure of obesity in elementary school children was really inappropriate, since the weight and height of these children continue changing inconsistently. In addition, generally available obesity related researches applied data mining techniques to help creating forecasting models by inserting data for training data sets and testing data sets, with only one format of input data, which is crispy value (Muhamad, Wahidah, & Nur, 2011; Nur, Nor, Nurulhuda, Fauzi, & Nur, 2016; Shaoyan, Chrristos, & Xiaojun, 2009). For example, a student weighs 30 kilograms and has a height of 150 centimeters, etc. As mentioned above, it was true that the input data should be diversified for applications with a variety of input data formats, especially, format of attributes explanation in ambiguous type so-called fuzzy attribute. Using linguistic term which is fuzzy linguistic term (Chittayasothorn, 2009) to interpret meanings of various fuzzy linguistic term e.g. about 30 kilograms, mean weight, low weight etc. To insert such data, it was not possible to apply the BMI as other researches in general, so this was obstacle for the calculation of obesity in school children.

Therefore, for this study, the researchers were interested in introducing a new concept of applying fuzzy logic (Zimmermann, 2001) with data mining techniques (Pang, Michael, & Vipin, 2006; Richard & Michael, 2003) to develop an obesity forecasting model using fuzzy data mining techniques. The sample of this study was primary school students in lower Northern provinces (Thailand). The researchers created a conceptual fuzzy database system to support fuzzy attributes data storage, and compared techniques work under the fuzzy neural network and fuzzy decision tree techniques. This new presented technique could improve the working of data mining by validating input data as fuzzy attributes in order to select the appropriate node to be used as new input data, which would be passed as input to work with creating system of forecasting model for the right model rules for further embedding code in the application. The input validation would be performed under all 3 input types, including crisp values, approximate values and fuzzy linguistic term values, respectively.

Methods and Materials

1. Compilation of factors related to the creation of obesity forecasting model

For factors influencing obesity, there were many researches mentioned the obesity in people aged more than 15 years. Most of these researches assessed the rate of obesity by BMI calculation, which is actual applicable to measure people aged over 20 years. This research focused on the factors influencing obesity in primary school students aged between 6 to 12 years, which is not necessary to only apply the BMI for measuring obesity but there are other factors causing obesity in Thailand. We found 2 major factors causing children obesity in Thailand, including heredity and environment. From preliminary information about heredity, we would found that families with obesity, especially obese mothers, have a greater risk of having obese children. For environmental factors, they could be divided into 2 parts, including consumption behavior factors and energy consumption behavior factors. This research used 950 samples of input from students in 125 primary schools in lower Northern provinces of Thailand, dividing into 3 school sizes, small, medium and large sizes according to the school grouping standards. The researchers set the initial inputs of 18 attributes, and 8 of the attributes were the qualitative Polytomous variables, so we needed to convert qualitative variables to be in a measurable format. That is to create these qualitative variables. For example, Career Parent, Education Parent and Class must be created in the form of Dummy variables. The researchers set the variables value to G-1, when G is the number of groups of variables as example shown in Table 1 showing dummy variables of class-level from primary school Grade1-6, by having the action of this class-level variable as a new set of G-1 Dichotomous variable, with G6 (Grade 6 students) as a reference group for comparison.

Table 1 Shows example of Dummy variable coding of class-level variables.

Group	**Class-level (Primary school)**	**X_1**	**X_2**	**X_3**	**X_4**	**X_5**
G1	Grade1	1	0	0	0	0
G2	Grade2	0	1	0	0	0
G3	Grade3	0	0	1	0	0
G4	Grade4	0	0	0	1	0
G5	Grade5	0	0	0	0	1
(Reference) G6	Grade6	0	0	0	0	0

2. Selection of input factors by using Pearson's correlation analysis

This research applied the principle of correlation analysis between variables to measure the value of variables in interval scale with Pearson's correlation calculation or sometimes called Simple Correlation, which was Bivariate Correlation, finding correlation between two variables. We called an independent variable as a predictor variable, and called dependent variable as a Criterion variable. Therefore, to select input factors, the researchers applied samples with sizes 20 times larger than the independent variables, and set Fat as a dependent variable. To calculate Pearson's Correlation Coefficient, the researchers used γ or γ_{xy} (as shown in Equation 1) to calculate the value of γ. In this research, the 22 independent variables that were transformed into quantitative variables were selected by considering values when $0.5 \leq \gamma \leq 1.0$. As shown in the example, the first 5 maximum variables included weight, height, level6, fast_food and congenital, which their values were 0.864, 0.824, 0.712, 0.711 and 0.689, respectively.

$$r_{XY} = \frac{N\sum XY - (\sum X)(\sum Y)}{\sqrt{\{N\sum X^2 - (\sum X)^2\}\{N\sum Y^2 - (\sum Y)^2\}}} \quad (1)$$

Where:

r_{XY} is Pearson's correlation Coefficient value

$\sum X$ is total sum of samples in X variable

$\sum Y$ is total sum of samples in Y variable

N is the number of samples in an attribute

3. Data storage with Fuzzy Database System through Natural language Information Analysis Method (NIAM)

For general research has avoid of data input in term of approximate value and fuzzy linguistic term value respectively. Therefore, the researchers aimed to use these 3 data format with the data usage by testing the forecasting function and results of obesity forecasting model. Meta-Knowledge Based and Conceptual Schema with NIAM technique was designed with Fuzzy attributes. In addition, this Meta-Knowledge Base would collect fuzzy values. Also, the designed Meta-Knowledge Base was developed from the NIAM technique (Figure 2) and mapped as a Relation schema to be used a Relational database (Nijssen & Halpin, 1989).

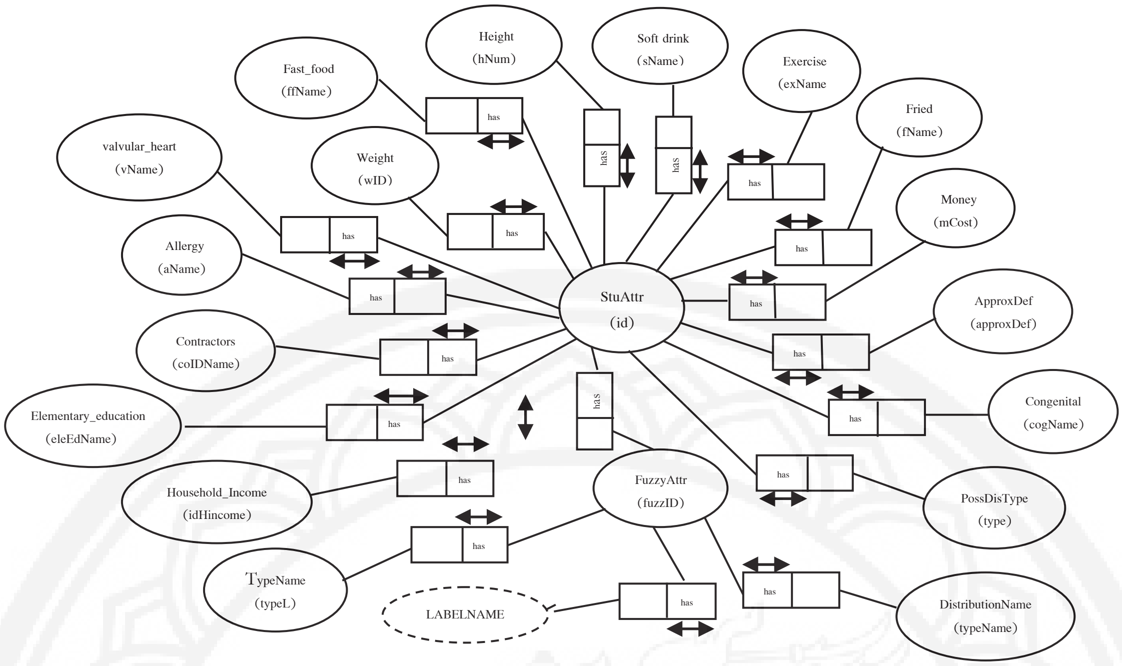

Figure 2 Shows some details of Meta knowledge based on conceptual schema.

4. Fuzzy data mining technique presentation

4.1 Principles of Fuzzy neural network and Fuzzy decision trees

This research has been implemented under the fuzzy attribute of weight, height, and value of family income in the aspect of Fuzzy linguistic term. There are 3 classes: High, Medium, and Low, respectively. This makes 3 nodes having been added as co-factors for predictive modeling in the attribute. Therefore, the forecasting model can support importing data to test the forecasts under three input data formats in this research. That is, the values of crisp, estimation, and with Fuzzy linguistic term, respectively, based on the concept of matching the value of the fuzzy attribute to be selected as the node agent to carry out calculations of the results of the forecast. The details of how the model performs that requires the import screening process as described above can be expressed with the Fuzzy neural network model and the Fuzzy decision tree model, respectively. Both algorithms were determined that the implementation of the input data under the same concept detailed (in Figure 3 and Figure 4 respectively) as follows:

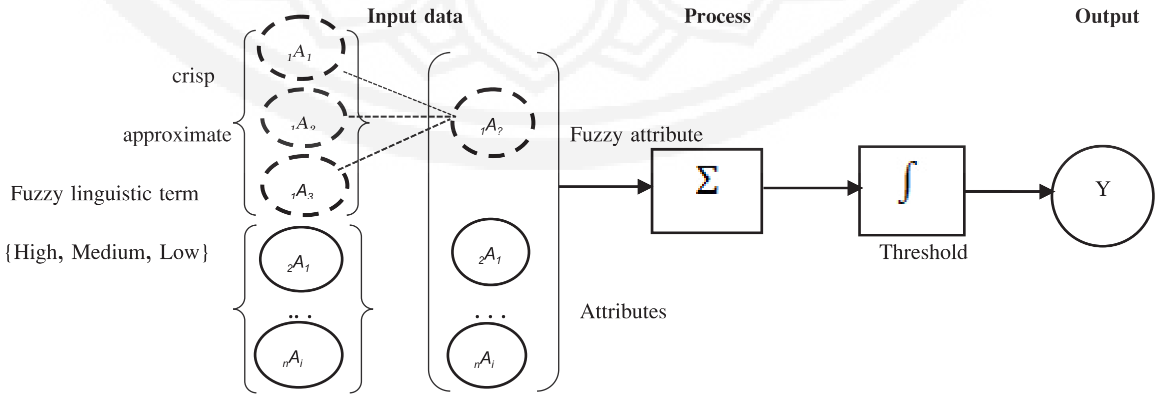

Figure 3 A Fuzzy neural network model

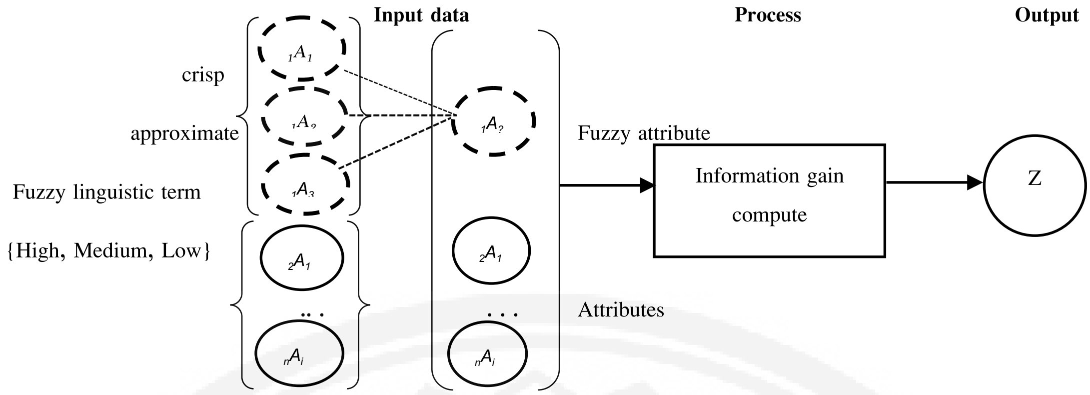

Figure 4 A Fuzzy decision trees model

4.2 Fuzzy attribute value representation

Data classification under the data mining technique presented in this research would compare between Decision tree and Neural net techniques that function in the form of Fuzzy logic to create a forecast volume of obesity, respectively. Before proceeding into the algorithm, the data from the decision trees and neural net would be adjusted according to the proportional profile of the individual student to the grade level of each school in the research. Therefore, the input data was likely to be fuzzy due to the answer being only predictions of the randomized student. General researches only use of the same data value under the function of the attribute value like the weight of the student defined as a number (Mariem, Slimane, Narjes, & Jacques, 2015; Raslapat & Prompong, 2016), such as a weight of 30 kilograms or a weight of 25 Kilograms, etc. In fact, the data values can be variously displayed. We present 3 types of data formats in this research (as shown in Table 1) even though they are the same attribute: for example, the student weight attribute would be shown in the Model 1, the Fuzzy linguistic term: high medium low, in line with the prescribed forms a trapezoid with the defined scope of the variable α, β, γ and δ respectively as the data sample displayed weight and height (as shown in Table 2 and Table 3 respectively). Model 2 was crisp value such as 35 kilograms weigh and Model 3 was the estimation such as roughly 25 kilograms, etc.

Table 1 The value of an attribute and fuzzy attributes

Attribute (Decision tree/ Neural net)		**Fuzzy attribute (Decision tree/ Neural net)**	
Weight(Kg.)	Height(cm.)	Weight(Kg.)	Height(cm.)
30	128	30	Approx128
25	130	Medium	130
38	137	Approx38	High

Table 2 The characteristics of Fuzzy linguistic term of attribute attr $_{11}$: "The weight of the student" (Unit: kilogram)

				DistributionName			
fuzzy ID	**label name**	**attrName**	**type**	α	β	γ	δ
0011	Weight	High	Trapezoidal	30	55	75	98
		Medium	Trapezoidal	21	26	31	37
		Low	Trapezoidal	10	12	18	23

Table 3 The characteristics of Fuzzy linguistic term of attribute attr $_{12:}$ " The height of the students (unit: centimeter)".

fuzzy ID	label name	attrName	type	DistributionName			
				$\propto$	β	γ	δ
0012	Height	High	Trapezoidal	140	148	155	165
		Medium	Trapezoidal	120	130	135	142
		Low	Trapezoidal	102	110	118	125

4.3 Fuzzy Attribute Matching Techniques

The concept of performing attribute values matching under appropriate modeling was presented in terms of the principle of matching input data into fuzzy attributes, including weight, height, and household income in this research. The data input can be fuzzy, approximated, or crisp, respectively. Therefore, the nature of matching under this research is as follows:

Model 1. Fuzzy attributes matching in terms of the Crisp value with Fuzzy linguistic term, which is comparing between the Crisp value and the Fuzzy linguistic term to check the degree of membership.

$$\mu(x{:}\,\alpha,\beta,\gamma,\delta) = \begin{cases} 1 \ when\ \beta \le x \le \gamma \\ 0 \ when\ x \le \alpha\ or\ x \ge \delta \\ \frac{\alpha - x}{\alpha - \beta}\ or\ \alpha < x < \beta \\ \frac{\delta - x}{\delta - \gamma}\ when\ \gamma < x < \delta \end{cases} \quad \text{Where } x \text{ is crisp value} \qquad (2)$$

Model 2. Fuzzy attributes matching the approximate value with Fuzzy linguistic term. The approx. χ would be defined using Triangle membership function by comparing to the fuzzy term, the 2 highest intersection of any member function with the equation conditions were as follows:

$$\mu(x, a{:}\,\alpha,\beta,\gamma,\delta) = \begin{cases} 1 \ when\ \beta \le x \le \gamma \\ 0 \ when\ x + a \le \alpha\ or\ x - a \ge \delta \\ \frac{\delta - x + a}{\delta - \gamma + a}\ when\ x > \gamma\ and\ x - a < \delta \\ \frac{x + a - \alpha}{a + \beta - \alpha}\ when\ x < \beta\ and\ x + a > \alpha \\ max(k_1, k_2);\ k_1 = \frac{x + a - \alpha}{(\beta - \alpha) + a}, k_2 = \frac{\alpha\text{-}}{(\beta\text{-}} \\ \quad when\ (x - a \ \ge \alpha\ \ and\ \alpha - x \le \beta) \end{cases}$$
$$or\ k_1 = \frac{\delta + x - a}{(\delta - \gamma) + a}, k_2 = \frac{\delta - x - a}{(\delta - \gamma) - a}$$
$$or\ (x + a \ \le \delta\ and\ \gamma < x < \delta)$$

Where:

x is the approximate of value

a is the margin value of the triangle function graph

Model 3. Fuzzy attributes matching the Fuzzy linguistic term with Fuzzy linguistic term by comparing the 2 values of the same attribute. The method of finding the degree of similarity between any two sets of fuzzy sets, we obtain the similarity result of the degree between the fuzzy expression pair that is greater than or equal to the t (Threshold) value.

$$S = k/(\frac{w_1-w_2}{\delta_1-\alpha_2} - k)$$

Where:

$$k = \frac{\delta_1-\alpha_2}{\delta_1-\gamma_1+\delta_2-\gamma_2}$$

$$w_i = w_{bi} + w_{ti}\ ; i = 1,2 \qquad (4)$$

$$w_{bi}(bottom\ width) = \frac{(\delta_i-\alpha_i)}{2}$$

$$w_{ti}(top\ width) = \frac{(\gamma_i-\beta_i)}{2}$$

Results

1. Comparing results of the fuzzy neural network and fuzzy decision tree

To finding the most appropriate model between fuzzy neural network and fuzzy decision tree. From the under dividing data to train and test with cross-validation folds and percentage split that can be shown in Table 4. The results shown that fuzzy neural network correctly value, precision value, recall value and f-measure at 84.3%, 82.7%, 84.3% and 82.8% respectively. So that, the appropriate models for predicting obesity were neural network algorithm with the neural network structure being 31-3-3, momentum at 0.2, learning rate at 0.3, data test with cross-validation folds = 10.

Table 4 Some of the under dividing data to train and test weight between the fuzzy neural network and fuzzy decision tree

Classifier		Test options	Correctly	Precision	Recall	F-Measure
Fuzzy decision tree	ID3	Percentage split20%	74.4	74.1	74.4	74.2
		Percentage split66%	75.2	73.8	75.2	74.4
		Cross validation 5-folds	79.0	79.5	79.0	79.2
		Cross validation 10-folds	79.5	80.1	79.5	79.7
	J48	Percentage split20%	81.5	71.0	81.5	75.2
		Percentage split66%	79.6	77.8	79.6	77.9
		Cross validation 5-folds	82.6	80.0	82.6	80.1
		Cross validation 10-folds	84.1	82.7	84.1	81.3
Fuzzy neural network	HN3	Percentage split20%	71.0	72.7	71.0	71.7
		Percentage split66%	78.4	75.0	78.4	75.9
		Cross validation 5-folds	82.8	81.9	82.8	81.6
		Cross validation 10-folds	84.3	82.7	84.3	82.8
	HN5	Percentage split20%	74.9	73.0	74.9	73.9
		Percentage split66%	79.0	77.2	79.0	77.8
		Cross validation 5-folds	80.1	77.7	80.1	78.6
		Cross validation 10-folds	83.2	82.6	83.2	82.4

Table 5 Some of the weight between the Input node and Hidden node

List of input node	Sigmoid Node3	Sigmoid Node4	Sigmoid Node5
Threshold	0.23	4.55	3.31
Sex	-1.72	-2.51	-1.45
C2 (Urban area)	-5.58	0.52	0.16
Level6	1.93	-5.65	2.33
Weight=Medium	1.50	6.87	5.11
Weight=low	-2.13	0.63	-18.24
Weight=High	0.40	-11.99	9.78
Allergy	0.36	-4.78	-1.53
Valvular_heart	-1.80	-3.38	-5.45
Normal	4.37	-0.91	-2.39
Congenital	-0.86	-4.43	-0.80

The weight values between the input node and the hidden node and between the hidden node and the output node as shown in Table 5 and 6 respectively.

Table 6 Some of the weight between the Hidden node and Output node

List of output node	Sigmoid Node0 (Normal)	Sigmoid Node1 (Fat)	Sigmoid Node2 (Thin)
Threshold	-10.83	7.73	-4.02
Sigmoid Node3	4.02	-4.81	-0.14
Sigmoid Node4	6.43	-12.03	4.82
Sigmoid Node5	8.51	-4.64	-3.54

2. Results of obesity prediction based on imported data under fuzzy data mining technique

The results of the obesity prediction of input data (as shown in Table 7) under the fuzzy data mining technique starting from the system of performing a fuzzy attribute lookup that needs to be adjusted: a fuzzy weight attribute was equal to "Approx32", a fuzzy height attribute was "Medium", and the fuzzy household income attribute was "Medium", respectively. Under the fat attribute, it was defined that Thin = 0, Normal = 1, and Fat = 2, respectively for the operation of the neural net that was 31-3-3 using the predictive import sample data with the attribute as follows:

Table 7 Samples of obesity forecast with fuzzy data mining techniques data

Sex	C2	Level6	Weight	Height	Allergy	Valvular_heart	Normal
1	0	0	Approx32	Medium	0	0	1
Congenital	**Exercise**	**Game**	**Money**	**Fast_food**	**Soft_drink**	**Candy**	**Fried**
0	1	0	1	2	2	2	2
Aunt	**Elementary_education**	**No_study**	**Contractors**	**Enterprise_employee**	**Household_Income**	**Fat**	
0	1	0	1	0	Medium	?	

The first step is to convert the data from the input data in Table with 31 input nodes, 3 hidden nodes and 3 output nodes. This research showed details only some of the attributes that compare to the node of the fuzzy model such as weight = "Approx32" compares the node level of "High" , "Medium", and "Low", respectively. The comparison details of Approx32 and Weight = "Medium" is presented in this research as follows:

The weight attribute was a1.

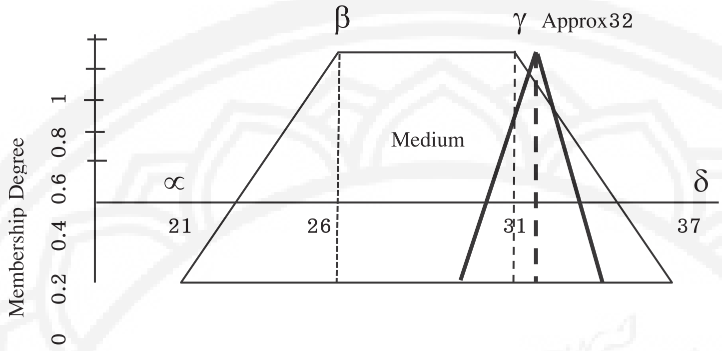

Figure 5 The comparison values of "Weight" between 'Approx32' with 'Medium'

Where:

x is the approximate of value

a is the margin value of the triangle function graph

$$\mu(x, a: \alpha, \beta, \gamma, \delta) = \begin{cases} 1 \; when \; \beta \le x \le \gamma \\ 0 \; when \; x + a \le \alpha \text{ or } x - a \ge \delta \\ \frac{\delta - x + a}{\delta - \gamma + a} \; when \; x > \gamma \; and \; x - a < \delta \\ \frac{x + a - \alpha}{a + \beta - \alpha} \; when \; x < \beta \;\; and \; x + a > \alpha \\ max(k_1, k_2); k_1 = \frac{x + a - \alpha}{(\beta - \alpha) + a}, k_2 = \frac{\alpha - x + a}{(\beta - \alpha) - a} \\ when \; (x - a \;\; \ge \alpha \;\; and \; \alpha - x \le \beta) \\ \qquad or \; k_1 = \frac{\delta + x - a}{(\delta - \gamma) + a}, k_2 = \frac{\delta - x - a}{(\delta - \gamma) - a} \\ \qquad or \; (x + a \;\; \le \delta \; and \; \gamma < x < \delta) \end{cases}$$

From Figure 5, we can compute the value for comparison between Approx32 and Medium.

- - - Approx32

—— Medium

so that

$$degree = \frac{\delta - x + a}{\delta - \gamma + a}$$

$$= \frac{37 - 32 + 3}{37 - 31 + 3}$$

$$= 0.89$$

Therefore, when calculating the comparison, it would be found that the approximation between Approx32 with "High", "Medium" and "Low" was 0.18, 0.89 and 0.0, respectively. Approx32 would be the weight of the fuzzy node, Weight = "Medium", which was equal to Sigmoid node3 = 1.50, Sigmoid node 4 = 6.87 and Sigmoid node5 = 5.11, respectively. This was done to calculate the neural net equation in the following step. The following step was to convert the input data for the neural net model test such as fuzzy weight attribute = "Approx32" with the details as follows: the value of the various attributes that have been converted into the equation for delivery to the active function as a node in the Hidden layer would be calculated are as follows.

Sigmoid node3 = x_1 = 1.00x(-1.72)-1.00x(-5.58)-1.00x(1.93)-0.43x(1.50)-0.21x(6.93)-1.00x(0.36)
-1.00x(-1.80)-1.00x(4.37)-1.00x(-0.86)-0.33x(6.71)-1.00x(-5.16)-1.00x(4.00)
+0.33x(0.81)+0.33x(-10.79)+0.33x(-6.85)+0.33x(-12.25)-1.00x(-3.46)
+1.00x(-4.88)-1.00x(2.35)+1.00x(-5.53)-1.00x(-2.63)+0.00(9.77)+0.23
= -19.33

$$f(x_1) = \frac{1}{1+e^{-x_1}} = \frac{1}{1+e^{19.33}} = 0$$

Sigmoid node4=x_2= 1.00x(-2.51)-1.00x(0.52)-1.00x(-5.65)-0.43x(6.87)-0.21x(0.24)-1.00x(-4.78)
-1.00x(-3.38)-1.00x(-0.91)-1.00x(-4.43)-0.33x(-4.73)-1.00x(4.13)
-1.00x(-1.23)+0.33x(-1.41)+0.33x(-5.43)+0.33x(-1.46)+0.33x(-7.98)
-1.00x(-5.50)+1.00x(1.93)-1.00x(5.04)+1.00x(1.08)-1.00x(3.01)+0.00(1.92)+4.55
= 11.42

$$f(x_2) = \frac{1}{1+e^{-x_2}} = \frac{1}{1+e^{-11.42}} = 1$$

Sigmoid node5=x_3= 1.00x(-1.45)-1.00x(0.16)-1.00x(2.33)-0.43x(5.11)-0.21x(-1.01) -1.00x(-1.53)
-1.00x(-5.45)-1.00x(-2.39)-1.00x(-0.80)-0.33x(7.69)-1.00x(5.93)-1.00x(-1.29)
+0.33x(3.86)+0.33x(-10.30)+0.33x(6.35)+0.33x(-8.07)-1.00x(-2.02)
+1.00x(-5.70)-1.00x(-5.26)+1.00x(5.39)-1.00x(0.81)+0.00(-0.75)+3.31
= -0.19

$$f(x_3) = \frac{1}{1+e^{-x_3}} = \frac{1}{1+e^{0.19}} = 0.45$$

After that, it enters the calculation node to present the result under the display of the 3 nodes, which were detailed.

Sigmoid node0=x_0 (Fat node : Normal node)= (0*4.02)+(1*6.43)+(0.45*8.51)-10.83 = -0.57

$$f(x_0) = \frac{1}{1+e^{-x_0}} = \frac{1}{1+e^{0.57}} = 0.36$$

Sigmoid node1 =x_1 (Fat node : Fat node) = (0*-14.81)+(1*-12.03)+(0.45*-4.64)+7.73 = -6.39

$$f(x_1) = \frac{1}{1+e^{-x_1}} = \frac{1}{1+e^{6.39}} = 0$$

Sigmoid node2 =x_2 (Fat node : Thin node) = (0*-0.14) +(1*4.82)+(0.45*-3.54) -4.02 = -0.79

$$f(x_2) = \frac{1}{1+e^{-x_2}} = \frac{1}{1+e^{0.79}} = 0.31$$

Therefore, from the calculation, it can be concluded that the sample used for the forecast system can predict the value of the Fat attribute close to Sigmoid node0 = χ_0. This was set to the "**Normal**" level because the result from the system could process with the highest value of 0.36.

Conclusion

From this research, the use of algorithms on the data mining techniques when is used with the obesity prediction model, it was found that many researches did not take input of each attribute, which should be varied and vague into account. They only used the same type of input data in each attribute. From this study, it was found that the problem was the limitation of using data mining techniques to create a model for predicting obesity. The results obtained from this study can solve the problem of vague importing data to be compatible with data mining techniques called "Fuzzy Data, Manning" by experimenting with the formulation of the obesity prediction model, obesity is mainly based on the principle of body mass indexing based on weight and height, but if that weight factor used "Approx32"and the height was" moderate ", etc., general research cannot be done when using the normal body mass index formula. Therefore, the principles presented in this research were able to solve such problems so it is especially useful for solving the problem of importing data in a vague format that works well with fuzzy neural network structure being 31-3-3 and correctly value, precision value, recall value and f-measure at 84.3%, 82.7%, 84.3% and 82.8% respectively.

References

Chittayasothorn, S. (2009). Toward fuzzy temporal databases with temporal fuzzy linguistic terms, The Second International Conference on the Applications of Digital Information and Web Technologies (ICADIWT2009), 2 October 2009 (pp. 8-13). http://dx.doi.org/10.1109/ICADIWT.2009.5273853

Ioannis, K., Maria, R., Maria, S., Emmanouil, B., Aikaterini, T., Kyriakos, S., & Greta, W. (2012). Prevalence of obesity in children aged 6-12 years in Greece: nutritional behaviour and physical activity. *Arch Med Sci, 8*(5), 859-864.

Mariem, J., Slimane, B. M., Narjes, B. B. S., & Jacques, D. (2015). Obesity determinants: A systematic review, Third World Conference on Complex Systems (WCCS), 2 June 2016 (pp. 1 – 6). http://dx.doi.org/10.1109/ICoCS.2015.7483277

Michael, B., Carolyn, G., Claudia, P., & Luciano, M. (2004). Overweight and obesity in 6-12 year old children in Switzerland. *Swiss Med Wkly, 134*(35-36), 523-528.

Muhamad, H., Muhamad, A., Wahidah, H., & Nur,'A. A. R. (2011). A framework for childhood obesity classifications and predictions using NBtree, 7th International Conference on Information Technology in Asia, 30 August 2011 (pp. 1 – 6). http://dx.doi.org/10.1109/CITA.2011.5999502

Nijssen, G. M., & Halpin, T. A. (1989). *Conceptual schema and relational database design.* Retrieved from https://www.amazon.co.uk/Conceptual-Schema-Relational-Database-Design/dp/0133557022

Nur,'A. D., Nor, L. M. N., Nurulhuda, N., Fauzi, M. S., & Nur, I. M. F. T. (2016). Predicting Obesity from Grocery Data: A Conceptual Process Framework , 6th International Conference on Information and Communication Technology for The Muslim World (ICT4M), 16 January 2017 (pp. 286 – 291). http://dx.doi.org/10.1109/ICT4M.2016.065

Pang, N. T., Michael, S., & Vipin, K. (2006). *Introduction to Data Mining.* Boston, MA, USA: Addison Wesley.

Richard, J. R., & Michael, W. G. (2003). *Data Mining A tutorial-Based Primer.* Boston: Addison Wesley.

Raslapat, S., & Prompong, S. (2016). A Knowledge Management Framework for Studying the Child Obesity, *International Conference on Industrial Engineering, Management Science and Application (ICIMSA)*, 5 July 2016 (pp.1 - 4). http://dx.doi.org/10.1109/ICIMSA.2016.7503983

Shaoyan, Z., Chrristos, T., & Xiaojun, Z. (2009). Comparing data mining methods with logistic regression in childhood obesity prediction. *Inf Syst Front, 11*(4), 449-460.

Zimmermann, H. (2001). *Fuzzy set theory and its applications.* Boston: Kluwer Academic Publishers.