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Fuzzy expert system design for detecting stunting

Linda Perdana Wanti[1], Oman Somantri[1], Nur Wachid Adi Prasetya[1], Lina Puspitasari[2]
[1]Department of Computer and Bussines, Politeknik Negeri Cilacap, Cilacap, Indonesia
[2]Department of Midwifery, Stikes Graha Mandiri Cilacap, Cilacap, Indonesia

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ABSTRACT

Stunting is a chronic nutritional problem that occurs in toddler due to lack of nutritional intake which results in impaired growth toddler. Usually, toddler who experience stunting are characterized by not increasing weight over a long period of time. Application utilization health which makes it easier for users to access information, one of which can be used to identify toddler who are stunted by selecting symptoms. The symptoms experienced by toddlers go through a system known as the system expert. In this research an expert system will be developed that is capable of early detection developmental disorders in toddlers using the Mamdani fuzzy method. The results obtained from this research are an expert system design for early detection of stunting using the Mamdani fuzzy method. The Mamdani fuzzy method was implemented to group the criteria for toddlers who fall into the stunting category or not from the initial data which is still gray because they are still unsure whether to categorize the toddler as having stunting or not. The detection accuracy rate using the Mamdani fuzzy method is 80.87% compared to expert diagnosis.

Corresponding Author:

Linda Perdana Wanti
Department of Computer and Bussines, Politeknik Negeri Cilacap
Cilacap 53212, Jawa Tengah, Indonesia
Email: linda_perdana@pnc.ac.id

1. INTRODUCTION

Stunting is a growth and development disorder in children under five which is identified by the nutritional status of children under five based on the PB/U or TB/U index which shows the measurement results are at the threshold of < -2 SD to -3 SD and < -3 SD in accordance with anthropometric assessment standards nutritional status of children [1], [2]. Stunting or short toddlers is caused by insufficient nutritional intake and occurs for quite a long time due to providing food that is not in accordance with nutritional needs and this creates conditions or problems of chronic malnutrition [3], [4]. The problem of stunting can start when the fetus is still in the womb and can only be identified when the toddler is two years old [5], [6]. If it is not balanced with catch-up growth in children under five who are identified as stunting, it can result in a reduction in growth and development in the growth of babies/toddlers, both motorically and mentally, which can increase the risk of illness and even death [7].

Based on the SSGI (Indonesian Nutritional Status Survey) conducted by the Ministry of Health in 2022, the prevalence value of children under five experiencing stunting in Indonesia reached 21.6% [8]. Data on children under five with stunting per province in Indonesia in 2022 is shown in graph Figure 1. Based on the data in the graph in Figure 1, the stunting prevalence value for Central Java Province is in 20th place with a value of 20.80% [9], [10]. The Cilacap Regency work program to reduce stunting rates involves all village midwives, program at village level to educate women on various aspects of family welfare (PKK) cadres and related agencies to intervene to accelerate the handling of stunting [11], [12].

An expert system is an information system in which there is expert knowledge in a specific field [13]-[15]. The aim of developing an expert system is to create a system that has the ability to recommend a series of actions to users to solve the problems faced [16]-[18]. Expert systems are able to project or predict an event by processing data to detect a disease based on the symptoms experienced by the patient based on a knowledge base and an inference engine which contains rules [19]-[22]. One use of an expert system is to diagnose children under five who are experiencing developmental disorders by detecting the symptoms they are experiencing such as not gaining weight, not increasing height, head circumference and others.

The benefit of this research is to detect early babies/toddlers who fall into the stunting category by identifying the symptoms experienced by the babies/toddlers and observing them over a certain period of time using an expert system that implements the Mamdani fuzzy method. The difference between this research and research that has been carried out by [23]-[27] is that the method used in this research is a Mamdani fuzzy method which clarifies a problem of uncertainty, inaccuracy and noisy as well as later, the symptoms in the expert system developed will be dynamic in nature and can be added or reduced, adjusted to real conditions in the field [28], [29]. The next update is that the expert system developed can later be used online so that the identification process can be carried out independently without being limited by space and time. The results of recommendations from the expert system developed, if babies/toddlers are indicated to be stunting, need to be treated and consulted further by pediatricians so that babies/toddlers get treatment quickly and appropriately. This expert system will support the performance of midwives and PKK cadres as well as related agencies in the process of monitoring babies/toddlers who have not experienced growth according to their age over a long period of time.

The novelty of this research is that the fuzzy method implemented will later be developed into an expert system that can help identify stunted babies or toddlers earlier because the variables used are taken from pregnant women so this can prevent stunting earlier compared to other research which takes variables to determine stunting in babies or toddlers where variables are taken by identifying the development of babies or toddlers over a certain period of time. The novelty of this research can also be seen from the use of an expert system where the expert system can be accessed by pregnant women to monitor fetal development from the first trimester to the third trimester so that if there are abnormalities during pregnancy they can be immediately identified and receive intensive treatment from health workers such as midwives and gynecologist doctors.

2. METHOD

A fuzzy inference system is a computational model based on fuzzy logic, which is a mathematical framework for dealing with uncertainty and imprecision [23]. Fuzzy logic allows for reasoning in situations where traditional binary logic (true or false) is insufficient, as it can handle degrees of truth between 0 and 1 [30]. Fuzzy logic is particularly useful in systems where the boundaries between different categories are not well-defined or when the system involves human expertise [31]. A fuzzy inference system consists of the following components such us fuzzification, fuzzy rule base, inference engine, defuzzification [32].

The fuzzy method is a method that uses logic that has a fuzziness value or vagueness value for a problem [33]. The fuzzy method is better known as fuzzy logic, because with this logic a value can be true or false at the same time [26]. To determine the truth value or error value, it is taken from the membership weights in the range 0 to 1 [34]. A problem that has an exact vagueness value is solved using Mamdani fuzzy logic because this logic is the most appropriate way to map the problem to the input space and then forward it to the output space and has a continuity value [35]. For Mamdani's fuzzy set theory, regions that have a range indicating the degree of membership are represented by language logic [36]. A set that is strictly defined, meaning that every element in the universe is clearly defined whether each element in it is part of its members or not is called a crisp set [16]. In this set there are strict and clear boundaries between elements that are members and elements that are not members of the set [37]. Linear representation is the process of mapping input to form a straight line representing the degree of membership [38].

Figure 1 explains the steps for developing a fuzzy expert system starting with defining the characteristics of the fuzzy model that will be developed functionally and operationally. After the model characteristics are finished, the process continues with composing the model and decomposing each variable used into fuzzy sets. The stage continues with the formation of rules used to define the defuzzification method. Then the next process is to run a system simulation before the system is tested to validate the results. In the decomposition process, variables are also defined regarding the system work matrix which is related to the system simulation. At the characteristic definition stage, post model normalization is also defined and connected to the production system that produces output from the fuzzy method.

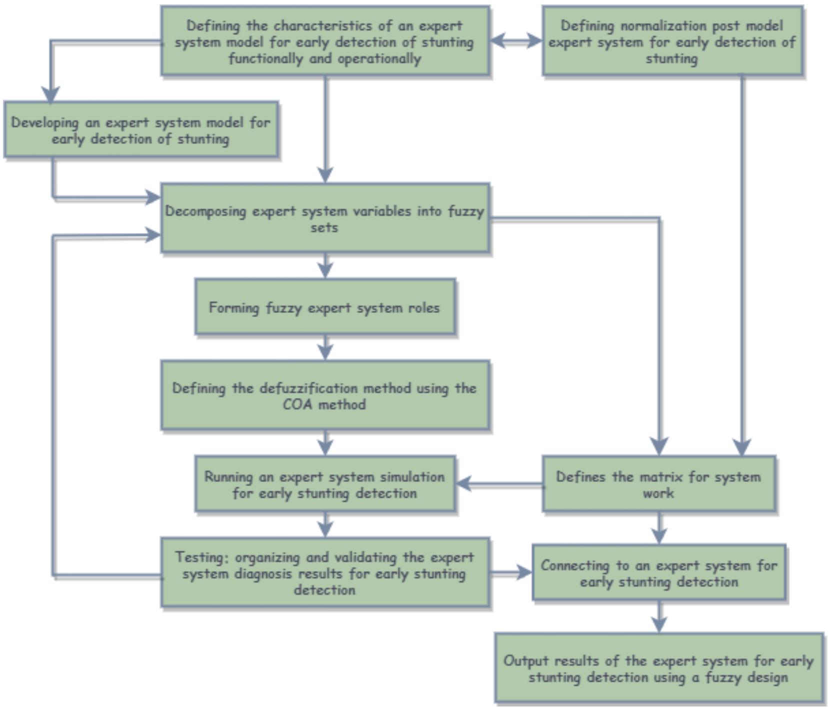

Figure 1. Mamdani fuzzy expert system design development stages

3. RESULTS AND DISCUSSION

This research uses data from the Cilacap District Health Service regarding babies or toddlers who are indicated to be stunted in Cilacap District in 2022. In 2022 the highest stunting rate was in Bunton village, Adipala District, Cilacap District. The mamdani fuzzy expert system design developed in this research begins with collecting data on toddlers who experience stunting by pulling it backward, starting from the process of pregnant women until the mother gives birth in Bunton village, Adipala subdistrict, Cilacap district for the period 2022 from January to December 2022. There is 37 pregnant women are coded into (IH1 to IH 37) with the specified variables. The data collection process starts from identifying mothers who give birth to babies with LBW (Low Birth Weight) who fall into the stunting category. Mothers who gave birth to LBW babies were recorded using variables obtained from experts, namely midwives and obstetricians. These variables include the age of pregnant women which is coded with "u", body mass index where body weight (kg) is divided by height (m) which is coded with "i", anemia suffered by pregnant women which are coded with "a", and the newborn's body weight (grams) which is coded with "b". Variable data, categories, μmin and μmax for each variable are shown in Table 1.

Table 1. Variables data, standards, and degree of membership for each variables

Variable	Category	Interval	μmin	μmax
Mother's Age (u)	Too Young	≤ 16	0.25	0.75
	Normal	$20 \leq u \leq 35$		
	Too Old	≥ 35		
Body Mass Index (i)	Underweight	≤ 24	0.2	0.8
	Normal	$25 \leq i \leq 35$		
	Overweight	≥ 40		
Anemia (a)	Heavy	≤ 7	0.4	0.6
	Currently	$7{,}1 \leq a \leq 8$		
	Light	≥ 10		
Baby Weight (b)	Low	≤ 2499	0.2	0.8
	Currently	$2500 \leq b \leq 3900$		
	More	≥ 4000		

The part of the expert system that functions as the center is the inference engine, where the task of the inference engine is to show the way for each reasoning process regarding a condition based on a knowledge base. In the inference engine, a manipulation process occurs that directs the rules, regulations, hypotheses, facts, symptoms stored in the knowledge base to reach certain conclusions. The first step in the fuzzy Mamdani method stage is to find the membership value of each variable. The output of the expert system design using the fuzzy Mamdani method is obtained from the inference engine. The output is converted into a firm value using the same membership function as when carrying out the fuzzification process.

3.1. Input variable

The following explains about the four input variables used in this research. The first is maternal age variable, the data is categorized into 3, namely mothers with a first pregnancy aged less than 16 years, mothers with a first pregnancy aged 20 to 35 years and mothers with a first pregnancy aged over 35 years. The second is body mass index variable, the data is categorized into 3, namely mothers with a body mass index below 25, mothers with a body mass index between 25 and 35 and mothers with a body mass index above 40. The third is anemia variable, the data is categorized into 3, namely pregnant women who are classified as having severe anemia, moderate anemia and mild anemia. And the last is newborn baby weight variable, the data is categorized into 3, namely babies born with a weight below 2,500 grams, babies born with a weight between 2,500 grams and 3,999 grams and babies born with a weight above 4,000 grams. Figure 2 shown in fuzzy variable set Figure 2(a) mother's age, Figure 2(b) body mass index, Figure 2(c) anemia, and Figure 2(d) baby weight.

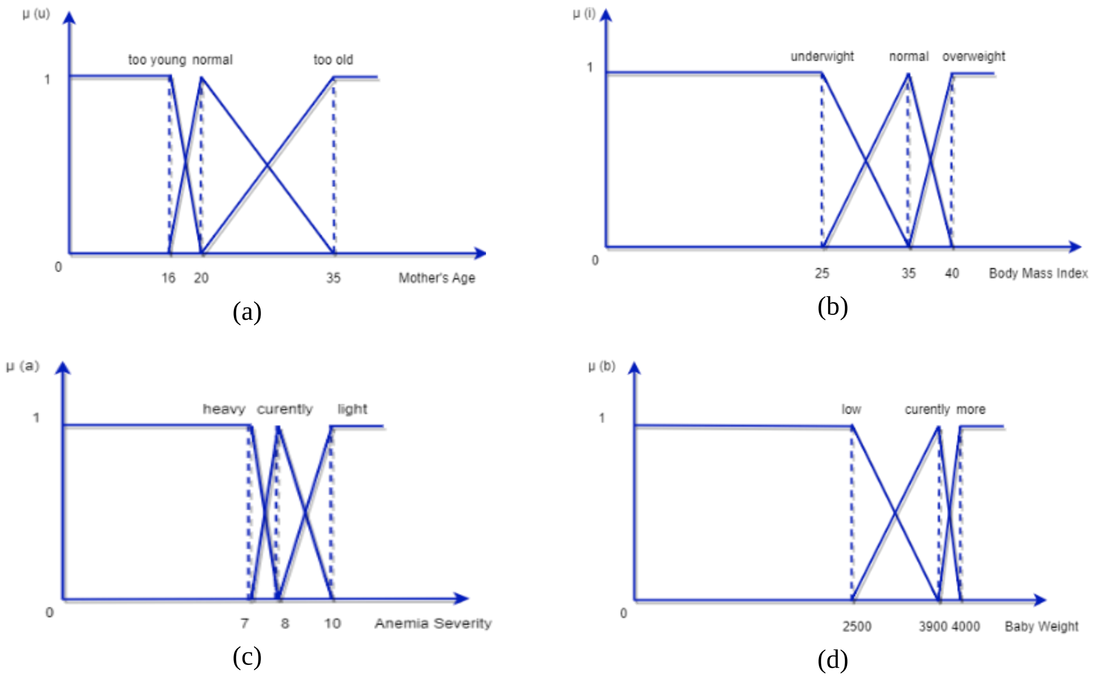

Figure 2. Fuzzy variable set (a) fuzzy variable set mother's age, (b) fuzzy variable set body mass index, (c) fuzzy variable set anemia, and (d) fuzzy variable set baby weight

3.2. Implementation in cases

Example of calculation for the first case of a pregnant mother at the age of 19 years with a body mass index of 24, the mother during pregnancy experienced mild anemia with an Hb of 8.4 and the baby was born weighing 2,350 grams. In the second case, the mother was pregnant at the age of 32 years with a body mass index of 21, the mother during pregnancy experienced moderate anemia with an Hb of 7.6 and the baby was born weighing 2,390 grams. The third case was a pregnant woman at the age of 42 years with a body mass index of 39, during pregnancy the mother experienced severe anemia with an Hb below 7, namely 6.3 and the baby was born weighing 2,200 grams. Below is the degree of membership for each set of variables from the three cases above as a sample of the implementation of the fuzzy method. Case 1 is shown in red, case two is shown in blue and case three is shown in green. Figure 3 fuzzy variable set Figure 3(a) mother's age, Figure 3(b) body mass index Figure 3(c) anemia, and Figure 3(d) baby weight.

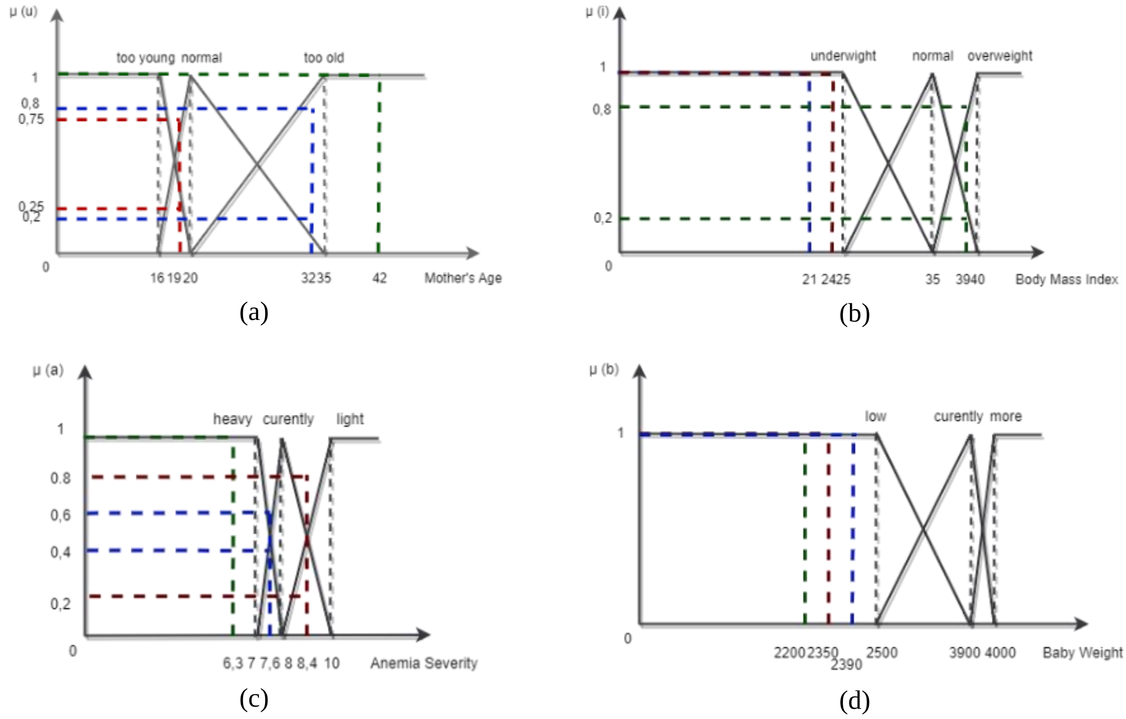

Figure 3. Fuzzy variable set (a) mother's age, (b) body mass index, (c) anemia, and (d) baby weight

After the definition activities above have been carried out, the next stage is the formation of an inference engine using (1). The following is the Mamdani fuzzy inference engine for the examples of case 1, case 2, and case 3 that are formed:

[R1] IF Mother’s Age (u) is too young AND Body Mass Index is underweight (i) AND Anemia is light (a) AND Baby Weight is low (b) THEN the toddler is INDICATED STUNTING
[R6] IF Mother’s Age (u) is too old AND Body Mass Index is normal (i) AND Anemia is light (a) AND Baby Weight is low (b) THEN the toddler is INDICATED STUNTING
[R7] IF Mother’s Age (u) is too young AND Body Mass Index is overweight (i) AND Anemia is heavy (a) AND Baby Weight is low (b) THEN the toddler is INDICATED STUNTING
[R10] IF Mother’s Age (u) is normal AND Body Mass Index is normal (i) AND Anemia is currently (a) AND Baby Weight is low (b) THEN the toddler is NOT INDICATED STUNTING
[R19] IF Mother’s Age (u) is normal AND Body Mass Index is normal (i) AND Anemia is currently (a) AND Baby Weight is normal (b) THEN the toddler is NOT INDICATED STUNTING
[R20] IF Mother’s Age (u) is normal AND Body Mass Index is overweight (i) AND Anemia is light (a) AND Baby Weight is low (b) THEN the toddler is INDICATED STUNTING

After knowing the min and max values, we look for the value of α-predicate and the value of z using (4) and (5) for each rule and the values for α-predicate and Z values are shown in Table 2.

Table 2. Degree of membership for each variable to the rule

Rule code	Result	α Value	Z Value
R1	IS	0.21	32.7
R2	IS	0.21	32.7
R3	IS	0.21	32.7
R6	IS	0.25	34.4
R7	IS	0.25	34.4
R10	IS	0.25	35
R13	IS	0.36	36.4
R14	IS	0.36	36.4
R17	IS	0.48	39.8
R18	IS	0.48	39.8
R20	IS	0.18	24.4

Composition of rules and affirmations use the max method to perform the composition. All the rules used are taken from each implication function in Table 2. The equation used for each variable is an equation to find the highest degree of membership or find the maximum value. The last step is to determine the value of z using the centroid method using (1).

$$Z = \frac{\sum \alpha_n z_n}{\sum \alpha_n} \quad (1)$$

$$Z = \frac{(0,21*32,7)+0,21*32,7)+\cdots+(0,18*24,4)}{0,21+0,21+\cdots+0,18} = 36,23$$

The defuzzification value of the babies or toddlers who are detected as stunting is:

$$36,23 * 100\% = 36,23\%$$

of the three cases in the example above, the first and third cases indicate stunting and the second case does not indicate stunting. The next process is to project all pregnant women and stunted babies according to the category of severity of stunting experienced. The defuzzification value for the category of babies or toddlers experiencing stunting is divided into four categories, namely i) mild with an interval of 0% to 25%, ii) moderate with an interval of 26% to 50%, iii) severe with an interval of 51% to 75%, and iv) very severe with an interval of 76% to 100% [28].

To calculate the level of accuracy between expert predictions and fuzzy method predictions, calculations were carried out using the mean percentage error (MPE) calculation [36]. In carrying out calculations using MPE for this case, expert prediction data is coded into expert prediction (EP) and prediction data using the fuzzy method is coded into fuzzy prediction (FP). The data is shown in Figure 4, then the calculation continues using the MPE calculation.

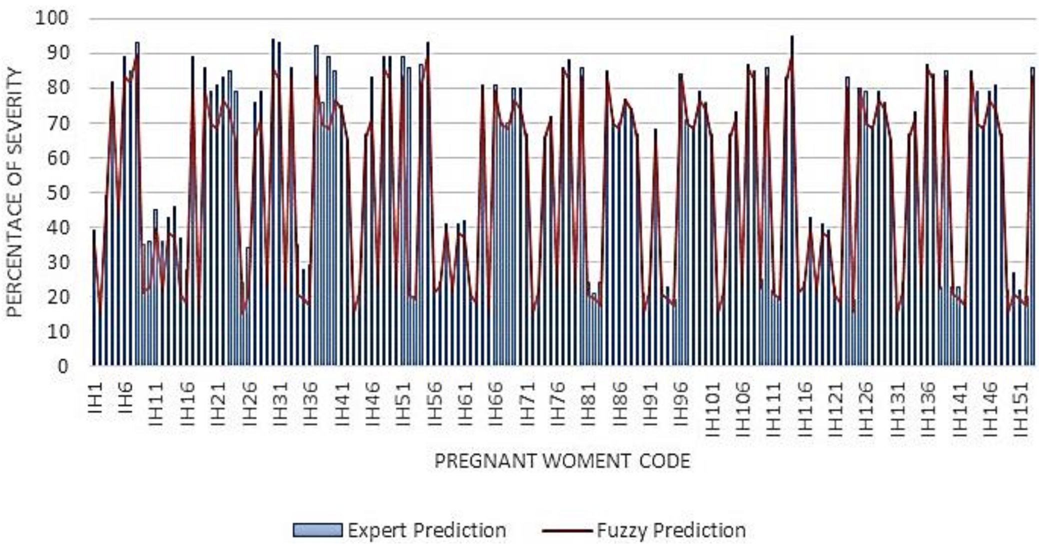

Figure 4. Comparation of expert prediction and fuzzy prediction

$$MPE = \frac{\sum_{t-1}^{n} \frac{a_t - a_t}{a_t} * 100\%}{n} \quad (2)$$

So, MPE for this case [37].

$$MPE = \frac{\sum_{t-1}^{n} \frac{2152 - 1836,8}{2152} * 100\%}{37} = \frac{707,9771}{37} = 19,1345175\%$$

For calculating the accuracy of expert predictions and predictions using the fuzzy method, it is:

$$100\% - 19{,}1345175\% = 80{,}8654825\%$$

based on the results of calculations using MPE calculations to calculate the level of accuracy of expert predictions, namely a pediatrician with predictions using the fuzzy method, it can be seen from 37 data on pregnant women with the variables maternal age, body mass index, Hb levels of pregnant women and birth weight of the baby. Accuracy rate of 80.87%. Meanwhile, the average value of the difference between expert predictions and predictions using the fuzzy method is 315.2 with the average error percentage from the fuzzy Mamdani method being 19.14%. Therefore, it can be concluded that the implementation of the fuzzy Mamdani method can be used to predict stunting in babies or toddlers using data from pregnant women with predetermined variables.

4. CONCLUSION

The conclusion obtained from this research is that the development of a fuzzy expert system design has been successfully carried out to detect early stunting based on predetermined variables such as mother's age, mother's body mass index, Hb level in the blood of pregnant women and birth weight of the baby. Based on Mamdani's fuzzy calculations, the defuzzification value for babies indicated as stunting was 36.23% from 37 data on pregnant women with predetermined variables. Based on the mean percentage error (MPE) calculation, the results of the diagnosis comparison between experts, namely pediatricians and the fuzzy expert system design, were obtained at 80.87% from 37 data on pregnant women. Meanwhile, the average value of the difference between expert predictions and predictions using the fuzzy method is 315.2 with the average error percentage from the fuzzy Mamdani method being 19.14%. These results mean that the fuzzy Mamdani design has been successfully implemented in an expert system for early detection of stunted babies or toddlers based on previously determined variables for pregnant women.

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BIOGRAPHIES OF AUTHORS

Linda Perdana Wanti was born in Banyumas, October 10, 1988. Currently working as a lecturer at the Cilacap State Polytechnic since 2019. She is scientist and lecturer at college of the Department of Cyber Security Engineering, State Polytechnic of Cilacap, Cilacap Regency, Indonesia. She received the Master of Computer Science (M.Kom.) degree in Informatics Engineering from Universitas Amikom Yoyakarta in 2013. Her research interests include machine learning for decision support system, database and expert system. She can be contacted at email: lindaperdana16@gmail.com.

Oman Somantri is scientist and lecturer at college of the Department of Cyber Security Engineering, State Polytechnic of Cilacap, Cilacap Regency, Indonesia. He holds a Master's degree in Informatics Engineering with a specialization in data science. His research areas are data mining, text mining, and sentiment analysis. He has received the S,Kom. degree in informatics engineering from the STMIK Sumedang, Indonesia, and the M.Kom. degree in informatics from the Universitas Dian Nuswantoro, Semarang, Indonesia. He can be contacted at email: oman_mantri@yahoo.com.

Nur Wachid Adi Prasetya was born in Wonogiri, November 15, 1988. Currently working as a lecturer at the Cilacap State Polytechnic since 2019. He graduated from Informatics Engineering at UIN Sunan Kalijaga Yogyakarta in 2011 and earned a Master of Computer Science (M. Kom) from the Master of Information Engineering at the University of Islam Indonesia in 2018. He has research interests in the field of image processing and information systems design. He can be contacted at email: nwap.pnc@pnc.ac.id.

Lina Puspitasari was born in Cilacap, October 26, 1990. Currently working as a lecturer at the STIKES Graha Mandiri Cilacap in Department of Midwifery since 2018. Her research is about obstetrics, pregnant women, preeclampsia, and facial massage in pregnant women. She graduated from Poltekkes Kemenkes Surakarta in 2014 and earned a Master of Public Health (M.P.H) from Sebelas Maret University in 2016. She can be contacted at email: lina_puspitasari@gmail.com.