Available *online* at : https://ejurnal.upnb.ac.id/index.php/JKPN

Jurnal Kesehatan

| ISSN (Print) 2085-7098 | ISSN (Online) 2657-1366 |

Mobile-Based Early Detection of Stunting by Using Risk Factors in Gunungkidul Regency, Special Region of Yogyakarta

Revita Susanti[1], Tri Sunarsih[2], Mohammad Hakimi[3], Siti Zakiah Zulfa[4], Rahmat Saputra[5], Desi Nindya Kirana[6]

[1,4,6] Faculty of Midwifery, Institut Kesehatan Payung Negeri Pekanbaru, Riau, Indonesia
[2] Faculty of Health, Universitas Jenderal Achmad Yani, Yogyakarta., Indonesia
[3] Faculty of Medicine, Public Health and Nursing, Universitas Gadjah Mada, Yogyakarta, Indonesia
[5] Faculty of Health and Informatics, Institut Kesehatan Payung Negeri Pekanbaru, Riau, Indonesia

ARTICLE INFORMATION

Received: 13 December 2025
Revised: 30 March 2026
Accepted: 19 June 2026
Available online: 30 July 2026

KEYWORDS

early detection; risk factors; stunting; data mining; C4.5 algorithm

CORRESPONDING AUTHOR

***Corresponding author, email:**
revitasusantii17@gmail.com

ABSTRACT

Background: In 2017, among 11 countries in Southeast Asia, Indonesia ranked second for the highest prevalence of stunting, reaching 36.4%. Early detection of stunting based on risk factors is essential to prevent stunting in children. **Objective**: To identify the risk of stunting by using a mobile-based application based on risk factors in Gunungkidul Regency, Special Region of Yogyakarta. **Methods**: This study employed an analytical survey with a cross-sectional design. The sample consisted of 98 mothers and their children aged 6–12 months, selected by using quota sampling. The stunting risk classification was performed by using data mining with the C4.5 algorithm to predict stunting status (at risk and not at risk). The data analysis included univariate analysis, validity testing of the D2S application (*Deteksi Dini Stunting*), and system feasibility testing. **Results**: The D2S application demonstrated 20% sensitivity (95% CI: 5.67%–50.98%), 97.73% specificity (95% CI: 92.09%–99.37%), and 89.79% accuracy. The feasibility test showed that 95% of the users accepted the application, indicating that it is highly feasible for use in the early detection of stunting. **Conclusion**: The mobile-based D2S application is a feasible tool with high specificity and good accuracy for early detection of stunting based on risk factors although its sensitivity remains low.

INTRODUCTION

In 2012, the WHO used the World Health Assembly as a platform to announce new nutrition goals, pledging to reduce stunting cases by 40% by 2025 [1]. Globally, in 2017, 150.8 million children under the age of 5 were stunted, with the highest incidence occurring in Asia (83.6 million children) and Africa (58.7 million children). Among the 11 countries in Southeast Asia, Indonesia ranked second for the highest incidence of stunting, at 36.4% in 2017 [2]. According to the Strategic Plan of the Ministry of Health (Decree No. HK.02.02/MENKES/52/2015), reducing stunting is a primary indicator. The 2015–2019 RPJMN targeted a decrease in stunting among children under two to 28% by 2019 [3]. Although the prevalence of stunting in Indonesia decreased to 30.8% in 2018, this figure still had not reached the national target of 28% [4]. In Yogyakarta, the prevalence of stunting rose from 11% in 2016 to 13.86% in 2017 [5] [6], with Gunungkidul Regency recording the highest rate at 20.60% [7]. Despite the declining trend, the prevalence of stunting in Indonesia and specifically in Gunungkidul Regency remains a significant public health concern as stunting continues to impair child growth and development [8].

The Scaling Up Nutrition (SUN Movement) is a global movement coordinated by the United Nations Secretary-General. The global goal of the SUN Movement is to reduce malnutrition, with a focus on the first 1,000 days of life. The Global SUN Movement indicators include a reduction in low birth weight (LBW), stunting, wasting, underweight, and overweight children [9]. Stunting is caused by several factors, including maternal factor, inadequate care, insufficient breastfeeding, inadequate complementary feeding, household environment, poor food quality, food and water safety, and infection [10]. Biological factors play a significant role; according to Sari et al. (2025), the risk of stunting at birth increases nearly sixfold in children whose parents are of short stature (mother <145.0 cm; father <161.9 cm) [11]. However, these risks are compounded by care practices. Kullu et al. (2018) demonstrate that maternal parenting patterns, especially regarding feeding, are significantly related to stunting in toddlers [12]. These feeding issues often stem from nutritional imbalances, such as the diets dominated by carbohydrates, the misperception that vegetables prioritize over animal protein, or the delayed introduction of protein due to allergy concerns [13]. Conversely, appropriate nutrition is protective; Uwiringiyimana et al. (2015) find that exclusive breastfeeding is significantly correlated with reduced stunting (OR: 0.22; 95% CI: 0.10–0.48) [14] while Kragel et al. (2025) confirm a significant difference in the mean HAZ between adequately nourished and malnourished groups (F: 7.069; p: 0.013) [15]. These biological and dietary factors are eventually exacerbated by poor environmental conditions, including unfit housing, air pollution, and inadequate sanitation, all of which significantly increase stunting risk [16]. The problems and consequences caused by stunting are divided into two categories: short-term and long-term [10]. Based on the results of the research by Undurraga, et al. (2017), stunted children have 18-21% and 15-21% lower probability of demonstrating mathematical and writing abilities than children who are not stunted. A cohort study by Wells et al. (2017) also reveal that children who are stunted at the age of 2 years have shorter legs, lower fat, and lean mass, and they have reduced kidney size and lung function at the age of 8 years [17]

Although various risk factors of stunting have been widely identified, early detection efforts in community settings remain limited. Most existing approaches focus on identifying stunting after it has occurred through anthropometric measurements rather than detecting the risk factors at an earlier stage. Current screening methods still have various limitations. The current stunting diagnosis process faces challenges, such as a lack of experienced health workers, incompatible anthropometric instruments, and an inefficient medical bureaucracy [18]. Furthermore, the use of universal height standards has the potential to lead to misclassification in certain populations due to differences in baseline growth characteristics [19]. Anthropometric measurements in children are also at risk of error due to limitations in the measuring instruments used, which can affect the accuracy of the results [20]. These conditions indicate that conventional stunting screening methods are still unable to comprehensively integrate various risk factors. Therefore, innovation is needed in the form of a risk factor-based stunting screening application such as D2S (*Deteksi Dini Stunting*) which can help health workers identify children at risk of stunting more quickly, accurately, and in an integrated manner to promote earlier preventive efforts.

The prevention of stunting focuses on children under two years of age and can begin during pregnancy or within the first 1000 days of life. Determining the factors that cause stunting in children can help identify specific interventions in the first 1000 days of life [21]. Therefore, it is necessary to conduct screening/early detection based on risk factors to prevent stunting in children. Early detection can prevent or overcome conditions or complications that occur [22]. Currently, technological advances, especially in the field of IT, have had a major impact on human life with various forms of artificial intelligence having

DOI: http://dx.doi.org/10.35730/jk.v17i2.1538

been created for use by human. Meanwhile, preventive measures in health can be taken by utilizing mobile technology.

The development of mobile technology has had a positive impact in various fields, including health. Mobile technology in the field of health, or mobile health (m-health), is a new paradigm that provides evidence, promise, and innovation in health technology [23]. In this context, a mobile-based approach can provide a more practical and accessible solution for early detection of stunting risk. Mobile-based applications can facilitate accurate data recording, standardize data entry, and provide real-time growth categorization to support early detection of stunting [8]. The C4.5 algorithm is a decision tree method widely used for classification and prediction [24]. Yunus et al. (2023) apply this algorithm to classify stunting in children and identify age as the most influential variable in the prediction model [25]. However, previous studies have mainly focused on prevalence analysis or single risk factor without integrating multiple determinants into a digital decision-support system. Therefore, this study develops a mobile-based application (D2S) by using the C4.5 algorithm for early detection of stunting based on multiple risk factors in Gunungkidul Regency, Special Region of Yogyakarta.

Based on the background of the problem, this study aims to identify the risk of stunting by using a mobile-based application based on risk factors in Gunungkidul Regency, Special Region of Yogyakarta.

METHODS

This study employed a cross-sectional approach combined with the development and validation of a mobile-based screening tool (D2S) for early detection of stunting risk. The data collection was conducted at a single point in time to examine the relationship between risk factors and stunting risk among children aged 6–12 months [26]. The population in this study was all mothers and their children aged 6-12 months in Gunungkidul Regency. The number of children aged 6-12 months in August 2018 in Gunungkidul Regency was 4,218 children. The sample size in this study was calculated by using the Slovin formula, resulting in 98 respondents. The sampling technique used in this study was the quota sampling. Quota sampling was selected to ensure proportional representation of respondents from the selected community health centers and to facilitate data collection within the limited study period and available resources. There were two selected health centers, Gedangsari II Community Health Center and Rongkop Community Health Center, with a sample distribution of 41 respondents in the working area of Gedangsari II Community Health Center and 57 respondents in the working area of Rongkop Community Health Center. As a non-probability sampling technique, quota sampling might introduce selection bias and limit the generalizability of the findings to the broader population. However, this method was considered appropriate for obtaining respondents who met the study criteria.

In this study, the researchers collected the samples through home visits. To obtain the samples, *door-to-door* visits were conducted at each respondent's home within the working area of each community health center. The inclusion criteria for this study were mothers with children aged 6-12 months, mothers who could read and write, and mothers who could communicate well. The exclusion criteria for this study were mothers who were unwilling to participate in the study, mothers who did not reside in Gunungkidul Regency, and mothers who were currently outside the city.

The variables in this study were the risk factors for stunting, including maternal height, maternal malaria infection, maternal worm infection, maternal HIV/AIDS infection, teenage pregnancy, birth spacing, low birth weight, premature birth, child-rearing patterns, early breastfeeding initiation, and exclusive breastfeeding as well as diarrhea infection, respiratory tract infection, malaria infection, and worm infection in children. The early detection of stunting was based on mobile-based risk factors and stunting incidents. The research instruments used were a family/household characteristics questionnaire, a stunting risk factor questionnaire, the D2S (Early Detection of Stunting) application, a child height measuring device, namely the WB-C Stature Gauge produced by GEA, a baby scale that has been calibrated with certificate number 4050/AMK/V/2019, and a user acceptance test questionnaire on the use of the D2S application consisting of 12 questions. The questionnaire was filled out by selecting the answers that corresponded to the opinions of 20 application users.

 DOI: http://dx.doi.org/10.35730/jk.v17i2.1538

In this study, validity testing was conducted by using the Pearson's product moment correlation with the aid of computerization. The validity testing was carried out in the working area of Semanu I Community Health Center because this working area has the highest incidence of stunting after that of Gedangsari II Community Health Center and Rongkop Community Health Center. The questionnaire used for the validity test was a questionnaire on child rearing patterns. This validity test was conducted with 30 respondents. In this study, two validity tests were conducted because the results of the first validity test showed that many questions were invalid, so the researcher conducted a second validity test on 30 other respondents.

The results of the first validity test of the parenting pattern instrument showed that out of 40 questions, 8 items were valid, 19 items were invalid, and 13 items had constant results; therefore, no validity test results were obtained from those 13 items. Then, a second validity test was conducted. Of the 17 items, 14 were valid and 3 were invalid. The reliability test used was the Cronbach's Alpha with the help of computerization. The reliability test results for the parenting style instrument were 0.761. These results indicated that the parenting style questionnaire used was reliable because the value was greater than 0.6.

In this study, the researchers collaborated with programmers to develop the D2S (Deteksi Dini Stunting) application for identifying stunting risk in children based on multiple risk factors. The D2S application was developed by using Flutter, an open-source framework for Android and iOS mobile applications. The respondent data entered through the application were stored in a MySQL database connected to an internet-based server. The application included some features related to stunting information and stunting risk assessment based on multiple risk factors.

The C4.5 algorithm was integrated into the application to generate decision trees and classification rules for categorizing children into stunting risk and non-risk groups based on the respondent data collected in this study. Based on the respondent data collected, the C4.5 algorithm analyzed 15 risk factors by calculating entropy and gain values to generate decision trees and classification rules for predicting stunting risk categories. The selected risk factors were based on the World Health Organization (WHO, 2017) and Hardinsyah & Supariasa (2016), which identified maternal, nutritional, environmental, and infection-related determinants associated with stunting in children [10], [21]. The operational definitions and categories of the variables used in the C4.5 classification process are presented in Table 1.

All the respondent data were directly used to generate classification rules by using the C4.5 algorithm because this study focused on the development and evaluation of a mobile-based screening application. This study conducted a univariate analysis, validity testing of the screening tool (D2S application) by using a 2×2 table to determine sensitivity, specificity, and accuracy values, as well as feasibility testing of the D2S application by using a user acceptance test questionnaire. The model validation was performed by comparing the classification results generated by the application with the respondent data collected in the study. This study also complied with ethical standards as evidenced by the ethical approval No. 989/KEP-UNISA/IV/2019.

DOI: http://dx.doi.org/10.35730/jk.v17i2.1538

Table 1 Operational Definitions and Categories of Stunting Risk Factors

No.	Variable	Operational Definition	Measurement Tool	Measurement Category
1	Maternal height	Maternal height recorded in the maternal and child health handbook (KIA)	Mobile application	1 = Short if height <145 cm 2 = Not short if height ≥145 cm
2	Maternal malaria infection	History of malaria infection experienced by the mother	Mobile application	1 = Yes 2 = No
3	Maternal helminth infection	History of helminth infection experienced by the mother	Mobile application	1 = Yes 2 = No
4	Maternal HIV/AIDS infection	History of HIV/AIDS infection experienced by the mother	Mobile application	1 = Yes 2 = No
5	Teenage pregnancy	Previous pregnancy occurring when the mother was in adolescence	Mobile application	1 = Yes, if the mother was pregnant at age 15–19 years 2 = No, if the mother was pregnant at age >19 years
6	Low Birth Weight (LBW)	History of infant birth weight <2500 grams recorded in the KIA handbook	Mobile application	1 = Yes, if birth weight <2500 grams 2 = No, if birth weight ≥2500 grams
7	Premature birth	History of childbirth at gestational age <37 weeks recorded in the KIA handbook	Mobile application	1 = Yes, if gestational age <37 weeks 2 = No, if gestational age ≥37 weeks
8	Birth spacing	Age interval between the current child and the previous child	Mobile application	1 = <2 years 2 = ≥2 years 3 = First child
9	Parenting pattern	Early childhood parenting pattern including nutrition, health, education, caregiving, supervision, and protection	Mobile application	1 = Inappropriate, if total score ≤ median 2 = Appropriate, if total score > median
10	Early Initiation of Breastfeeding (EIBF)	Implementation of breastfeeding initiation within the first hour after birth	Mobile application	1 = No, if EIBF was not performed within the first hour after birth 2 = Yes, if EIBF was performed within the first hour after birth
11	Exclusive breastfeeding	Provision of breast milk only without additional food or drinks until the infant reached 6 months of age	Mobile application	1 = Non-exclusive breastfeeding, if additional food/drinks were given before 6 months 2 = Exclusive breastfeeding, if only breast milk was provided until 6 months
12	Child diarrhea infection	History of diarrhea experienced by the child within the last 2 months	Mobile application	1 = Yes 2 = No
13	Child acute respiratory infection (ARI)	History of ARI experienced by the child within the last 2 months	Mobile application	1 = Yes 2 = No
14	Child malaria infection	History of malaria infection experienced by the child	Mobile application	1 = Yes 2 = No
15	Child helminth infection	History of helminth infection experienced by the child	Mobile application	1 = Yes 2 = No

DOI: http://dx.doi.org/10.35730/jk.v17i2.1538

RESULTS AND DISCUSSION

Frequency Distribution of Respondent Characteristics

Table 2 Frequency Distribution of Respondent Characteristics

Respondent Characteristics	Number (n=98)	%
Mother's Age		
<20 years	5	5.1
20-35 years	72	73.5
>35 years	21	21.4
Total	**98**	**100**
Mother's Highest Level of Education		
No schooling	1	1.0
Primary education	52	53.1
Secondary Education	39	39.8
Higher Education	6	6.1
Total	**98**	**100**
Mother's occupation		
Working	16	16.3
Not working	82	83.7
Total	**98**	**100**
Mother's ethnicity		
Javanese	97	99
Sundanese	1	1
Total	**98**	**100**
Monthly Family Income		
Low Income	78	79.6
High Income	20	20.4
Total	**98**	**100**
Child Nutrition Status		
Severe malnutrition	1	1.0
Underweight	7	7.1
Well-nourished	90	91.8
Total	**98**	**100**
Delivery		
Cesarean section	29	29.6
Normal	69	70.4
Total	**98**	**100**
Child's Gender		
Male	51	52
Female	47	48
Total	**98**	**100**

The characteristics of the respondents were mostly aged 20-35 years, totaling 72 people (73.5%). Of the 98 respondents, the highest level of education was elementary school (elementary school, junior high school, Madrasah Tsanawiyah), totaling 52 people (53.1%). Of the 98 respondents, most of the respondents were unemployed, totaling 82 people (83.7%). In terms of the mother's ethnicity, most of the respondents were Javanese, reaching 97 people (99%). Based on the monthly family income, families with low incomes (<

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IDR 1,571,000) outnumbered families with high incomes, reaching 78 people (79.6%). Of the 98 respondents, most of the children were well-nourished, namely 90 people (91.8%). Based on the birth process, most of the respondents gave birth normally, namely 69 people (70.4%). Of the 98 respondents, most of the children were male, reaching 51 people (52%).

Incidence of Stunting in Children

Table 3 Frequency Distribution of Respondents Based on Stunting Incidence in Children

Incidence of Stunting	Number (n=98)	%
Severely stunted	1	1.0
Stunted	9	9.2
Not stunted	88	89.8
Total	**98**	**100**

Based on Table 3, it is known that 1 child (1.0%) is severely stunted, 9 children (9.2%) are stunted, and 88 children (89.8%) are not stunted.

Data Mining Results for Early Detection of Stunting Based on Risk Factors

Data mining is a process that employs one or more machine learning techniques to analyze and extract knowledge automatically [27]. As an integral part of Knowledge Discovery in Databases, this process focuses on uncovering previously unknown patterns and relationships within vast datasets (Hemlata, 2018). Fundamentally, data mining utilizes statistical models, mathematical algorithms, and learning techniques to automatically enhance its performance [28].

In this study, to identify categories of stunting risk in children based on risk factors, data mining was used with the C4.5 algorithm. Using the C4.5 algorithm on respondent data, a decision tree was formed. In the decision tree technique, the patterns or information obtained from the data mining process are in the form of rules obtained from the decision tree that has been constructed. The following are the rules obtained from the decision tree shown in Table 4.

Tabel 4 Rules

No	Rules
1	If mother_height='not short' then status='not at risk of stunting'
2	If mother_height='short' and parenting_style='inappropriate' then status='at risk of stunting'
3	If mother_height='short' and parenting_pattern='appropriate' then status='not at risk of stunting'

The following are the results of the validity test between the results of early detection of stunting and the results of PB/U measurements to determine sensitivity and specificity by using a 2x2 table.

Table 5 Validity Test

Early Detection of Stunting Results	Measurement PB/U		Number
	Stunting	Not Stunted	
At risk	2	2	4
Not at risk	8	86	94
Total	10	88	98

Description:

a (True Positive): Children classified as *at risk* and truly stunted

b (False Positive): Children classified as *at risk* but actually not stunted

c (False Negative): Children classified as *not at risk* but actually stunted

d (True Negative): Children classified as *not at risk* and truly not stunted

 DOI: http://dx.doi.org/10.35730/jk.v17i2.1538

$$\text{Sensitivity} = \frac{a}{a+c} \text{ x } 100\%$$

$$= \frac{2}{2+8} \text{ x } 100\%$$

$$= \frac{2}{10} \text{ x } 100\%$$

$$= 20\%$$

$$\text{Specificity} = \frac{d}{b+d} \text{ x } 100\%$$

$$= \frac{86}{2+86} \text{ x } 100\%$$

$$= \frac{86}{88} \text{ x } 100\%$$

$$= 97.73\%$$

$$\text{Accuracy} = \frac{a+d}{a+b+c+d} \text{ x } 100\%$$

$$= \frac{2+86}{2+2+8+86} \text{ x } 100\%$$

$$= \frac{88}{98} \text{ x } 100\%$$

$$= 89.79\%$$

Table 6 D2S Application Diagnostic Test

No	Output	Value	95% CI*	
			Minimum	Maximum
1	Prevalence	10.20%	5.64%	17.77%
2	Sensitivity	20.00%	5.67%	50.98%
3	Specificity	97.73%	92.09%	99.37%
4	Positive Predictive Value	50.00%	15.00%	85.00%
5	Negative Predictive Value	91.49%	84.10%	95.62%
6	Positive Likelihood Ratio	8.80	1.39	55.83
7	Negative Likelihood Ratio	0.82	0.60	1.12

A 95% confidence interval can be used to describe the precision of an estimate by placing it within a range of values consistent with the data. The narrower the confidence interval, the more precise the estimate [29]. In this study, the sensitivity value was 20%, with a 95% confidence interval of 5.67% and 50.98%, indicating that the estimate was imprecise and varied widely. This low sensitivity suggests that a large proportion of children who were actually stunted were not identified by the D2S application.

In the context of screening, sensitivity is particularly important because the primary goal is to identify as many true cases as possible and minimize missed cases. Therefore, the low sensitivity observed in this study indicates that the application was not yet optimal as a screening tool. This limitation may lead to delayed identification and intervention for children with stunting.

Several factors may explain the low sensitivity observed. First, the imbalance in the dataset, where the number of non-stunted children (n = 88) is much higher than that of stunted children (n = 10), may affect the ability of the model to recognize patterns of stunting. Second, the limited number of risk factors

DOI: http://dx.doi.org/10.35730/jk.v17i2.1538

used in the model may not fully capture the complexity of stunting conditions. In contrast, the specificity was high at 97.73%, with a relatively narrow 95% confidence interval (92.09%, 99.37%), indicating that the application performs well in identifying children who are not stunted. Predictive value refers to the probability/likelihood that subjects with positive test results are actually sick or that subjects with negative results are actually healthy [30]. In this study, the positive predictive value (PPV) was 50%, indicating that only half of the children identified as at risk were actually stunted. Therefore, positive screening results should be confirmed with more accurate diagnostic methods. Meanwhile, the negative predictive value (NPV) was 91.49%, indicating that most of the children identified as not at risk were indeed not stunted. This suggests that the application is more reliable in identifying non-stunted children than in detecting stunting cases.

Feasibility Test of the D2S Application System for Early Detection of Stunting

Table 7 Frequency Distribution of Respondents Based on the Feasibility Test of the D2S Application System for Early Detection of Stunting

Feasibility	Number (n=20)	%
Very Feasible	19	95
Suitable	1	5
Fairly Good	0	0
Not Fair	0	0
Total	**20**	**100**

Based on Table 7, the results of the D2S application system feasibility test in detecting the risk of stunting in children show that 19 respondents (95%) stated that it was very feasible and 1 respondent (5%) stated that it was feasible. Therefore, it can be concluded that this application is very feasible to use based on the feasibility test of 20 application users.

Prevention of stunting in children focuses on children under two years of age and can begin during pregnancy or within the first 1000 days of life. The golden period for optimal stunting prevention in children can begin from preconception, pregnancy, and infancy (Saleh Ariyanti, et al 2021) [31]. Identifying the factors that cause stunting can help identify specific interventions in the first 1000 days of life [21]. Therefore, it is necessary to conduct screening/early detection based on risk factors to prevent stunting in children.

Early detection can be done by using a mobile application. The researchers collaborated with programmers in creating the D2S (Deteksi Dini Stunting) application to detect the risk of stunting in children based on their risk factors. The researchers also collaborated with programmers in determining the stunting risk categories in children by using the C4.5 data mining algorithm.

Based on the results of the data mining process, three rules were found and could be used to predict the risk of stunting in children. The first rule can be interpreted as meaning that if a mother is not short (≥145 cm), then it is likely that her child will not be at risk of stunting. The second rule indicates that if a mother is short (<145 cm) and has inappropriate parenting practices, then it is highly likely that her child is at risk of stunting. The third rule indicates that if a mother is short (<145 cm) and has appropriate parenting practices, then it is highly likely that her child is not at risk of stunting. These results align with a study of 50,372 children (34.5% of whom are stunted), in which maternal height predicts growth more strongly than paternal height. The risk of stunting is higher for short mothers (aRR=1.89) than for short fathers (aRR=1.56) but increases threefold when both parents are short (aRR=3.23) [32].

These rules can help predict whether a child is at risk of stunting or not. From the explanation of the rules above, it is known that the risk factors used as rules to detect the risk of stunting in children are the mother's height and child-rearing patterns. The mother's anthropometry is also related to stunting in children. Based on the results of research by Aguayo, et al. (2016) [33], children born to mothers with a height below 145 cm have twice the chance of experiencing stunting. Mothers with good parenting patterns tend to have toddlers with better nutritional status than mothers with poor parenting patterns [34]. This is in line with the results of research by Kullu, et al. (2018), which show a significant relationship between

 DOI: http://dx.doi.org/10.35730/jk.v17i2.1538

maternal parenting and the incidence of stunting in toddlers [12]. Because stunting causes go beyond diet to include social factors, prevention must also prioritize parental education and better parenting skills [35]. While eating patterns do not always directly correlate with nutritional status [36], this suggests that child health relies on a broader framework where maternal factors are dominant [37]. Maternal knowledge significantly predicts dietary intake and health outcomes [38], often exerting a stronger influence than paternal education [39], [40]. Notably, maternal education especially beyond the secondary level remains a positive predictor of nutritional status independent of socioeconomic factors. This underscores maternal knowledge as a critical, independent determinant of child health [41], [42]. For instance, nutritional education programs have been shown to significantly improve maternal knowledge of stunting prevention in various contexts [43]. Similar research also shows that to address stunting issues, a combination of programs such as home visits combined with other programs, one of which is the Women's Group Participatory Learning and Action for group mentoring for women parents, has proven effective in addressing nutritional health issues in children [44].

Based on the results of the research conducted on 98 respondents, there were 10 children who experienced stunting, consisting of 1 child who was severely stunted and 9 children who were stunted, while 88 children were normal. Based on the results of data mining by using the D2S application, it was found that out of 98 respondents, 4 children were at risk of stunting, consisting of 2 children who were at risk of stunting and actually experienced stunting, and 2 children who were at risk of stunting but did not experience stunting based on PB/U. From the D2S application, it was found that 94 children were not at risk of stunting, consisting of 8 children who were not at risk of stunting but actually experienced stunting and 86 children who were not at risk of stunting and did not experience stunting based on PB/U.

In this study, the evaluation process was conducted by using a 2x2 validity test table, which yielded sensitivity and specificity values as well as accuracy values from the data mining results. The sensitivity value from this study was 20%, and the specificity value was 97.73%.

Sensitivity, also known as 'recall' in machine learning, measures the ability of a test to correctly identify positive cases and minimize false negatives [45], [46], [47]. A diagnostic tool is generally considered sensitive if it exceeds a 60% threshold [30]. In medicine, high sensitivity is prioritized to ensure all true positives are detected, even at the cost of higher false positives [48]. Based on the sensitivity value obtained, the D2S application built based on data mining with the C4.5 algorithm was less sensitive in detecting children at risk of stunting, with a sensitivity value of 20%. The sensitivity value of 20% in this study may have occurred because the number of children experiencing stunting was smaller than the number of children who were not stunted, and the risk factors used in this study were only 15 risk factors. In this study, the number of children who were actually sick (stunted) was small, only 10 children, while the number of children who were not sick (stunted) was 88 children. If this study had been conducted with a larger number of children experiencing stunting, the results would likely have been more sensitive.

The risk of stunting based on the D2S application with height/age measurements differs because it is viewed from the risk factors possessed by the respondent. If the height/age measurement results indicate stunting but the D2S results do not indicate a risk of stunting, this is because the respondent does not have risk factors that correspond to the rules found in this study.

Low sensitivity indicates that the test will miss many individuals who have the disease. In this study, this means that the detection of stunting risk would miss many children who actually experienced stunting. In the epidemiological jargon, it is said that screening with low sensitivity will increase the number of false negatives [49]. False negatives indicate those who are sick but are declared negative based on test results [45]. In this study, the total number of children who were stunted based on height-for-age measurements but were declared negative/not at risk of stunting based on test results was 8 children.

False negatives have consequences that can be detrimental to patients. The consequence of a false negative is that patients will feel safe, when in fact they have the disease. As a result, diagnosis is delayed and the necessary treatment is not administered, leading to increased morbidity and mortality as well as higher costs [50]. Although the sensitivity value of the D2S application was 20%, it successfully detected children who were truly ill (stunted) even though there were only 2 children.

Based on the specificity value obtained, the D2S application built based on data mining with the C4.5 algorithm had a high specificity value of 97.73%, which met the minimum criteria according to Budiarto

DOI: http://dx.doi.org/10.35730/jk.v17i2.1538

(2004) in Susetyowati (2015), which is 70% [30]. Specificity is the ability of a test to accurately identify individuals with negative results who are not sick or the ability to determine people who are not sick [45]. Specific tests rarely err in determining that a person does not have a disease (Fletcher, 1996 in Susetyowati, 2015) [30]. The specificity value of this study shows that the D2S application can be used very well in determining children who are not at risk of stunting. A highly specific test means that there are few false positives [51]. False positives are those who test positive but are not actually sick [50]. In this study, only two false positives were found. The results of this study can be used to detect the risk of stunting with an accuracy rate of 89.79%. Tests with high specificity perform well for diagnosis because they have low false positives. Meanwhile, tests with low specificity have disadvantages, including the large number of people without the disease who will test positive and potentially receive unnecessary (and possibly invasive, risky, or expensive) follow-up diagnostic or therapeutic procedures [51]. In this case, screening with high specificity will avoid the consequences caused by tests with low specificity that will be detrimental to the individual.

Many other studies have also applied data mining processes in predicting diseases, such as the study conducted by Muzakir and Wulandari (2016), which uses data mining to predict hypertension in pregnancy [24]. Andriani, A (2013) also conducts research on a decision tree-based diabetes prediction system by using data mining [52]. This data mining process is also applied in the research conducted by Abdillah, S (2015), who studies the application of the C4.5 decision tree algorithm for the diagnosis of stroke with data mining classification at the Santa Maria Hospital in Pemalang [53].

Previous studies have developed Android-based and smart-system applications for stunting prevention and early detection, primarily focusing on anthropometric monitoring, child growth and development assessment, balanced nutrition education, and parenting interventions [54], [55]. The BERAKSI application, for example, is designed to assist parents and health cadres in monitoring child growth, development, balanced nutrition, and parenting practices through several educational menu features [54]. Similarly, the smart-system application developed by Muflihatin (2024) focuses mainly on early detection of stunting based on anthropometric standards and nutritional status assessment in toddlers [55].

However, unlike previous applications, the D2S application integrates the C4.5 data mining algorithm to classify stunting risk based on multiple maternal and child risk factors rather than relying solely on anthropometric measurements. In addition to providing educational information and health monitoring features, the D2S application generates decision rules for risk classification and includes validity testing using sensitivity, specificity, and accuracy measurements, thus enabling more comprehensive and objective screening for early detection of stunting risk. Therefore, the D2S application not only functions as an educational and monitoring tool but also as a mobile-based screening system that supports earlier identification of children at risk of stunting before anthropometric abnormalities become apparent.

The results of this study are presented in the form of a mobile application called D2S (Early Detection of Stunting), which can be used easily, quickly, and accurately by mothers. This application can be used to detect early on whether a child is at risk of stunting. The application also includes two modules:

1. YUK KESSINI (Yuk Kenali Stunting Sejak Dini), a module that contains comprehensive information about stunting.
2. Perbaiki Pola Asuh, Sukses Tangani Stunting Pada Anak!, a module that provides information on managing stunting in children.

The D2S application was developed by using Flutter, an open-source framework developed by Google to build Android and iOS application user interfaces (UI). The data sent from the D2S application are stored in a MySQL database and can be accessed from anywhere with an internet connection. With the MySQL database stored on the server, the data can be easily accessed through applications and other media connected to the internet. The other media referred to can be other smartphone devices or other applications because the MySQL database can be integrated with other applications, thus allowing the development of various applications in the future. The features developed in this application are information about stunting and stunting risk assessment based on risk factors.

The D2S application has undergone an application system feasibility test using a user acceptance test questionnaire consisting of 12 questions. This system feasibility test was conducted on 20 users to assess

 DOI: http://dx.doi.org/10.35730/jk.v17i2.1538

the working system of the application. The application system feasibility test shows that the majority of the respondents stated that this application is very feasible to use in detecting the risk of stunting in children. This meets several indicators of the suitability of an application system, namely the suitability indicator of the D2S application in helping to detect the risk of stunting, the suitability indicator of information in the D2S application, the suitability indicator of the D2S application for the needs of detecting the risk of stunting in children, the indicator of the benefits of using the D2S application, the indicator of the capabilities and functions of the D2S application, the indicator of the use of the D2S application, the D2S application display design indicator, the font size indicator in the D2S application, the font and background color indicator in the D2S application, the language usage indicator in the D2S application, the obstacle indicator when using the D2S application, and the indicator of the feasibility of questions about the risk of stunting in children in the D2S application.

This study, however, has several limitations. The relatively small sample size and the limited number of stunted children might affect the sensitivity and generalizability of the findings. In addition, the study was conducted only in selected community health center areas in Gunungkidul Regency, which might not fully represent broader populations. Future studies are recommended to involve larger and more diverse populations and include additional risk factors to improve the predictive performance of the application.

Conclusion

Based on the results of this study, the D2S (Deteksi Dini Stunting) application has the potential as a mobile-based screening tool for early detection of stunting risk in children. Although the application demonstrates low sensitivity in detecting children at risk of stunting, it shows high specificity and accuracy in identifying children not at risk. This study is limited by a relatively small sample size and a limited number of stunted children, which may have affected the sensitivity and generalizability of the findings. Therefore, it is recommended that future research involves a larger and more varied population as well as includes more risk factors to improve the application's predictive performance. The D2S application can support community health workers, midwives, and primary health care programs in conducting more efficient early screening and monitoring of stunting risk, particularly in community and primary health care settings.

ACKNOWLEDGEMENTS

The authors express their highest appreciation to the Ministry of Higher Education, Science, and Technology (Kemendiktisaintek) for the financial support provided through the 2025 Reputable Journal Publication Assistance scheme. The authors also wish to thank all the respondents for their time and valuable data contribution.

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