SOCIOECONOMIC ANALYTICS

Stunting Prediction Model Based on Health, Social, and Economic Factors Using Genetic Programming in Coastal Areas of East Java Province, Indonesia

Agus Dwi Sulistyono [1] *
Waego Hadi Nugroho [2]
Loekito Adi Soehono [2]

[1] Department of Socio-Economy Fisheries and Marine, Faculty of Fisheries and Marine Sciences, Universitas Brawijaya, Indonesia. Email: agusdwistat@ub.ac.id. * corresponding author

[2] Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Brawijaya, Indonesia
Email: whn@gmail.com, loekito_mat@ub.ac.id

RESEARCH ARTICLE

Socioeconomic Analytics
https://periodicos.ufpe.br/revistas/SECAN/
ISSN Online: 2965-4661

Submitted on: 23.11.2026.
Accepted on: 31.05.2026.
Published on: 13.07.2026.

Abstract

Stunting is a failure to achieve optimal growth in children under five, especially during the first 1000 days of life, caused by chronic maternal and early-life nutritional deficiencies. Indonesia ranks fourth globally in stunting prevalence. This study examined 650 newborns, their mothers, families, and environmental conditions in East Java, Indonesia. The dependent variable was stunting incidence, while 26 independent variables encompassed maternal health before and during pregnancy, paternal health conditions, economic status, environmental quality, and maternal nutritional intake during pregnancy. Symbolic regression (Genetic Programming) was applied to analyze the influence of these determinant factors. Model selection was based on R^2, F1-score, accuracy, and several additional performance metrics. Data processing was conducted using SPSS and HeuristicLab 3.3. Results indicated that the symbolic regression model performed exceptionally well, with $R^2 = 0.951$ for the training set and $R^2 = 0.999$ for the testing set. Prediction accuracy reached 99.17% (training) and 100% (testing). Other classification indicators consistently demonstrated the model's high precision and stability. The most influential variables contributing to stunting incidence included the father's respiratory disease history, paternal smoking behavior, maternal body mass index, maternal hemoglobin level during pregnancy, iron intake, vegetable protein intake, animal protein intake, and milk consumption. Among these, animal protein consumption emerged as the most dominant protective factor, where higher and adequate intake substantially reduced the likelihood of stunting in newborns. These findings highlight the strong predictive capability of symbolic regression and reinforce the importance of maternal nutrition and household health conditions in preventing stunting.

Keywords

Newborn; Prediction; Stunting; Symbolic Regression

1. Introduction

Based on data from the Ministry of Health's Basic Health Research (Riskesdas) in 2019, before the COVID-19 pandemic, 6.3 million Indonesian toddlers were experiencing stunting out of 23 million toddlers in Indonesia. This figure is ranked 4th in the world with a prevalence of 27.7%, which is still far from the WHO standard value (<20%). During the COVID-19 pandemic, the refocusing of the COVID-19 budget was the cause of reduced funds for handling stunting national programs, which had an impact on stunting reduction, and the prevention of malnutrition did not reach the target. This condition also makes the target of reducing the stunting rate by 14 percent by 2024 difficult to achieve (Ryandi, 2020).

Of the 38 regencies/cities in East Java Province, in 2018, the highest prevalence of stunting occurred in Bondowoso Regency, reaching 56.38% of toddlers who were weighed. In 2019, the East Java Provincial Government focused on stunting handling in 12 districts/cities, namely Bangkalan, Sampang, Pamekasan, Sumenep, Jember, Bondowoso, Probolinggo, Nganjuk, Lamongan, Malang, Trenggalek, and Kediri (Dinas Komunikasi dan Informatika Pemerintah Provinsi Jawa Timur, 2019).

The main factor causing stunting is malnutrition or chronic disorders in children (Wahdah, Juffrie, & Huriyati, 2016). This happens because of the lack of knowledge of mothers about the intake given to children, especially related to improving the nutritional status of children (Ibrahim, 2014). The problem of malnutrition in children with stunting must receive serious attention from the community, and has even become a government program to overcome stunting problems (Renyoet, Hadju, & Rochimiwati, 2013). The incidence of stunting in children often occurs in communities with low levels of education (Olsa, Sulastri, & Anas, 2018).

Research on the factors that influence stunting in various regions has been carried out. From these studies, it is shown that the factors of birth weight, nutritional status, parental education, sanitation, infection, and economic status are closely related to the incidence of stunting (Bentian, Mayulu, & Rattu, 2015; Kusumawati, Rahardjo, & Sari, 2015; Lestari, Margawati, & Rahfiludin, 2014; Rochmah, 2017; Setiawan, Machmud, & Masrul, 2018; Sulastri, 2012; Wellina, Kartasurya, & Rahfilludin, 2016). The most important nutritional content influencing the occurrence of stunting is zinc deficiency (Aridiyah, Rohmawati, & Ririanty, 2015),(Wessells & Brown, 2012). Research on stunting in various countries has also been carried out with several approaches. Among them is the socio-economic and demographic approach (Flores-Quispe, Restrepo-Méndez, Maia, Ferreira, & Wehrmeister, 2019; Gatica-Domínguez, Victora, & Barros, 2019; Restrepo-Méndez, Barros, Black, & Victora, 2015; Said-Mohamed, Micklesfield, Pettifor, & Norris, 2015), with an environmental study approach (Hagos, Lunde, Mariam, Woldehanna, & Lindtjørn, 2014; Lloyd, Sari Kovats, & Chalabi, 2011; Vilcins, Sly, & Jagals, 2018), and a linear modeling approach (Cooper et al., 2019; Khan & Mohanty, 2018; Takele, Zewotir, & Ndanguza, 2019). This study was conducted to develop a symbolic regression classification model to predict the incidence of stunting in East Java, Indonesia. The results of the modeling and classification of stunting events with the Symbolic Regression approach will be used as an early warning system for consideration by the government or other researchers in making policies or programs related to the reduction in the incidence of stunting in East Java based on location.

2. Methods

This study uses primary data using a survey at the research partner's place, namely the Independent Practice Midwife, in several cities/districts of East Java. This study uses 26 independent variables and one dependent variable. The dependent variable studied was the incidence of stunting (Y). The independent variables studied included maternal blood pressure before pregnancy (X1), maternal diabetes before pregnancy (X2), maternal body posture (X3), father's blood pressure (X4), father's diabetes disease (X5), father's respiratory disease (X6), Father's Posture (X7), Father's Cigarette Consumption (X8), Family Income (X9), Clean Water Source (X10), House Floor (X11), Sanitation (X12), Frequency of Pregnancy Checkup (X13), Weight Development (X14), Body Mass Index (X15), Upper Arm Circumference (X16), Maternal Blood Pressure During Pregnancy (X17), Hb Level During Pregnancy (X18), Urine Protein (X19), Age of Birth (X20), Fe Consumption (X21)), Consumption of Vegetable Protein (X22), Consumption of Animal Protein (X23), Consumption of Milk (X24), Consumption of Vitamins (X25), Consumption of Noodles/Meatballs (X26).

The research sample observed included 650 newborns, mothers, and family environments across several high-prevalence districts in East Java, Indonesia, specifically focusing on areas such as Lamongan, Probolinggo, Jember, Malang, Nganjuk, and Kediri. This selection ensures adequate representation of both coastal and inland communities facing significant stunting challenges. The data collected from these locations is divided into two sets for the modeling process: 600 samples were utilized as training data to develop and optimize the Genetic Programming model, and the remaining 50 samples were reserved as testing data to validate the model's predictive accuracy and generalization capability.

Bivariate testing to determine the relationship between the independent and dependent variables was initially performed using the Chi-Square test. The core novelty of this research lies in the Genetic Programming (GP) modeling using a Symbolic Regression approach for classification. The performance of the resulting model is comprehensively measured by calculating the coefficient of determination (R^2), as well as various metrics derived from the confusion matrix, including the F1-score, Positive Predictive Value (PPV), Negative Predictive Value (NPV), and overall accuracy. The entire analysis process was executed using SPSS 25.0 software and the HeuristicLab 3.3 optimization environment.

3. Results and Discussion

The study was conducted on 650 newborns in several high-prevalence districts in East Java, Indonesia. Of the 650 newborns, 140 cases of stunting were found, and 510 were normal. The following are the characteristics of the research sample:

Table 1: Characteristics of the research sample

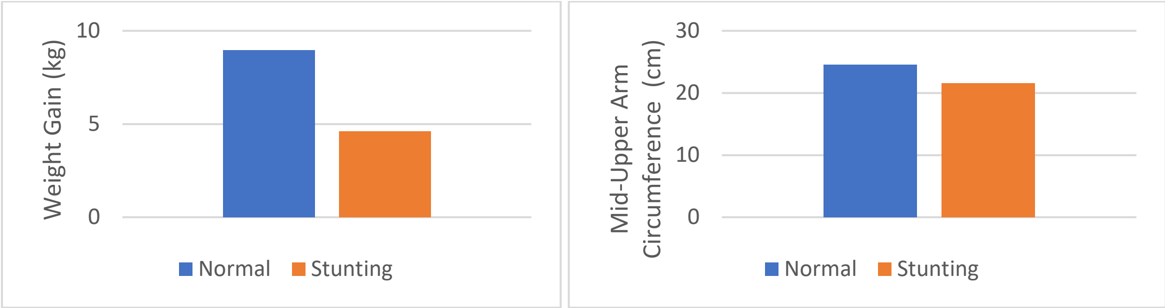
Characteristics	Stunting Incident	
	Normal (n=510)	Stunting (n=140)
Mother's Blood Pressure Before Pregnancy		
Normal	417 (64.2%)	17 (2.6%)
Abnormal	93 (14.3%)	123 (18.9%)

Mother's Blood Pressure During Pregnancy		
Normal	453 (69.7%)	4 (0.6%)
Abnormal	57 (8.8%)	136 (20.9%)
Maternal Diabetes Before Pregnancy		
No	454 (69.8%)	94 (14.5%)
Yes	56 (8.6%)	46 (7.1%)
Maternal Body Mass Index During Pregnancy		
Normal	430 (66.2%)	0 (0%)
Abnormal	80 (12.3%)	140 (21.5%)
Father's Blood Pressure		
Normal	467 (71.8%)	52 (8%)
Abnormal	43 (6.6%)	88 (13.5%)
Father's Diabetes		
No	457 (70.3%)	51 (7.8%)
Yes	53 (8.2%)	89 (13.7%)
Father's Cigarette Consumption		
Not/often	436 (67.1%)	22 (3.4%)
Heavy	74 (11.4%)	118 (18.2%)
Family Income		
Low	435 (66.9%)	55 (8.5%)
High	75 (11.5%)	85 (13.1%)
Clean Water Source		
Good	433 (66.6%)	39 (6%)
Not good	77 (11.8%)	101 (15.5%)
House floor		
Good	457 (70.3%)	53 (8.2%)
Not good	53 (8.2%)	87 (13.4%)
Sanitation		
Good	468 (72%)	58 (8.9%)
Not good	42 (6.5%)	82 (12.6%)

Based on the characteristics of the research sample in Table 1, it is shown that mothers who had abnormal blood pressure before pregnancy were more at risk of giving birth to stunting babies. Of the 140 stunting babies, 123 mothers had abnormal blood pressure. Likewise, the mother's blood pressure during pregnancy. Stunting babies are more common in pregnant women who have abnormal blood pressure. On the characteristics of the history of diabetes in the mother before pregnancy, of 140 cases of stunting babies, 94 babies were born to mothers who did not have a history of diabetes. This proves that a history of diabetes is not a determinant of stunting.

Judging from the characteristics of diabetes in the father, among 140 stunting infants, there were 89 stunting infants whose fathers had a history of diabetes. Likewise, on the characteristics of cigarette consumption in fathers, it is shown that the majority of stunting infants have fathers who smoke heavily. Descriptively, it was shown that the father's history of diabetes and cigarette consumption were the determinants of stunting.

Environmental factors also contribute to stunting. From this study, it was shown that from 140 stunting infants, the majority of clean water sources, house floors, and poor sanitation.



(a) (b)

Figure 1. Characteristics of weight gain (a) and Mid-Upper Arm Circumference (b)

Judging from the characteristics of maternal weight gain during pregnancy, it was shown that the average weight gain of mothers who gave birth to stunting babies was lower than mothers who gave birth to normal babies. Likewise, the upper arm circumference of mothers with stunted infants is smaller than that of normal mothers. Descriptively, it was shown that the factor of low maternal weight gain and lower maternal upper arm circumference during pregnancy had an impact on the incidence of stunting.

3.1. The Result of Bivariate Data Analysis

Bivariate data analysis was carried out to determine the relationship between the determinant factors and the incidence of stunting. The analysis was carried out using the Chi-Square test. The following are the results of testing the relationship between the determinant factors and the incidence of stunting:

Table 2: Bivariate analysis of the relationship between determinant factors and stunting incidence

Variables	Chi-Square	p-value	Variables	Chi-Square	p-value
Maternal Blood Pressure Before Pregnancy (X1)	202.623	0.000	Weight Development (X14)	360.809	0.000
Maternal Diabetes Before Pregnancy (X2)	24.272	0.000	Body Mass Index (X15)	325.547	0.000
Mother's Posture (X3)	8.275	0.004	Upper Arm Circumference (X16)	347.266	0.000
Father's Blood Pressure (X4)	176.783	0.000	Maternal Blood Pressure During Pregnancy (X17)	379.713	0.000
Father's Diabetes (X5)	161.925	0.000	Hb Levels During Pregnancy (X18)	353.653	0.000
Father's Respiratory Disease (X6)	222.19	0.000	Urine Protein (X19)	390.227	0.000
Father's Posture (X7)	0.308	0.579	Age of Birth (X20)	85.095	0.000
Father's Cigarette Consumption (X8)	228.791	0.000	Consumption of Fe (X21)	335.857	0.000
Family Income (X9)	111.217	0.000	Consumption of Vegetable Protein (X22)	362.908	0.000

Clean Water Source (X10)	178.394	0.000	Consumption of Animal Protein (X23)	314.949	0.000
House Floor (X11)	147.541	0.000	Milk Consumption (X24)	191.476	0.000
Sanitation (X12)	154.706	0.000	Consumption of Vitamins (X25)	140.046	0.000
Frequency of Pregnancy Checkup (X13)	27.067	0.000	Consumption of Noodles/Meatballs (X26)	145.231	0.000

Based on the results of the bivariate test, information was obtained that the variable Father's Posture (X7) had a p-value of 0.579 ($p>0.05$). From this test, it was shown that there was no significant relationship between the father's posture and the incidence of stunting. Or, in other words, the father's posture is not a determining factor for stunting. Therefore, the process of estimating the stunting prediction model was carried out on 25 determinant factors that had a significant relationship ($p<0.05$).

3.2. The Result of Symbolic Regression Models

The formation of a classification model for stunting in newborns is carried out based on the evaluation of model possibilities as many as 1,000,000 models with a mutation probability of 15% and several generations of 1000. The following are the R2 values, accuracy, and MSE of the model built:

Table 3: R^2 value, accuracy, and MSE model

Performance Measure	Data Training	Data Testing
R^2	99.17%	100%
Accuracy	0.951225	0.998803
MSE	0.00791	0.000442

The following is a symbolic regression model for the classification of stunting infants obtained:

$$Y = \exp\left(\frac{\left(\left(\left(\left(\frac{\frac{0.986X_{22}}{0.078X_{15}}}{17.927} \cdot \left((0.967X_{23})^{18.002} + (0.967X_{23})^{18.929} \right) - \frac{(0.963X_{21})^{17.035}}{\left((0.986X_{22})^{-17.78} + \frac{0.986X_{22}}{0.078X_{15}} \right)} \right) - \frac{(0.987X_{24})^{18.002}}{(0.963X_{21})^{-17.78} \cdot (0.986X_{22})^{17.035}} \right)\right)\right)^{2}}{\left(\frac{-4.805}{\left(\frac{0.986X_{22}}{0.078X_{15}} + \left((0.986X_{22})^{18.083} - (-7.93 + 2.237X_{7}) \right) \right)} + \left(\frac{(0.998X_{8})^{18.002}}{\frac{(1.42X_{6})^{\frac{1}{-17.78}}}{(0.254X_{16})^{17.035}}} + \left(18.929 - (0.254X_{16})^{17.035} \right) \right) \right) \cdot 1.946X_{18}} \right)$$

Based on the stunting prediction model with symbolic regression, it is shown that of the 25 independent variables entered as determinants of stunting, 8 variables have the most dominant influence. The following is the impact weight of these variables:

Table 4 Impact variables of the symbolic regression model

Independent Variables	Impact Variables
Consumption of Animal Protein (X23)	0.812308
Consumption of Fe (X21)	0.809231
Body Mass Index (X15)	0.804615
Hb Levels During Pregnancy (X18)	0.803077
Milk Consumption (X24)	0.063077
Consumption of Vegetable Protein (X22)	0.010769
Father's Cigarette Consumption (X8)	0.004615
Father's Respiratory Disease (X6)	0.001538

Based on the value of the impact variable, it is shown that the Animal Protein Consumption variable has the highest impact variable value. From this test, it is proven that the consumption of animal protein has a dominant influence on stunting cases. The better the consumption of animal protein, the lower the chance of stunting. The next variables that have a big impact are Fe consumption, Body Mass Index, and Hb levels during pregnancy. The following is a confusion matrix of training data and testing data in classifying stunting infants:

Table 5: Confusion matrix for stunting prediction results

	Actual Training Data	
Prediction of Training Data	Normal	Stunting
Normal	474	0
Stunting	5	121

	Actual Testing Data	
Prediction of Testing Data	Normal	Stunting
Normal	31	0
Stunting	0	19

Based on the training data confusion matrix table, it was shown that from 479 normal babies, the prediction results obtained 474 normal babies, and there were only 5 prediction errors. Meanwhile, in 121 stunting babies, 121 babies were found that matched the predictions, and there were no prediction errors. In the confusion matrix data testing table, it is shown that from 31 normal babies, the prediction results obtained 31 normal babies and 19 stunting babies; it was predicted that there were 19 stunting babies. The following is the performance measure value from the symbolic regression model:

Table 6: Performance measure score model symbolic regression

Performance Measure	Score
F1 score (test)	1.0
F1 score (training)	0.995
False discovery rate (test)	0%
False discovery rate (training)	0%
False positive rate (test)	0%
False positive rate (training)	0%
Matthews Correlation (test)	1.0
Matthews Correlation (training)	0.975

Negative predictive value (test)	100%
Negative predictive value (training)	96.03%
Positive predictive value (test)	100%
Positive predictive value (training)	100%
True negative rate (test)	100%
True negative rate (training)	100%
True positive rate (test)	100%
True positive rate (training)	98.96%

Based on the performance measurement score above, the F1 score is 0.995 in the training data and 1.0 in the testing data. This proves that the model obtained has a very high level of accuracy in classifying stunting events. Likewise, when viewed from the performance coefficient Positive Predictive Value (PPV) and Negative Predictive Value (NPV) of 100% and 96.03% on training data and 100% on testing data. This means that the model is very sensitive in classifying positive stunting and normal infants.

3.3. Discussion

Based on the results of the classification modeling of stunting, it was shown that not all determinants had a significant effect on stunting cases. Although family income, sanitation, and frequency of pregnancy checkups showed significant associations with stunting in the bivariate analysis, these variables were not among the dominant predictors retained in the final symbolic regression model. This finding suggests that their effects may be mediated through other health and nutritional factors included in the model. Different from Nguyen (2014) and Kusrini (2021) research has proven that an increase in family income has a positive effect on the increase in the birth weight of babies. The insignificant effect of the frequency of pregnancy checkups indicated that the role of midwives in assisting pregnant women during the first checkup needed to be improved. Counseling for pregnant women, especially for chronic lack of energy, needs to be addressed (Goisis, Remes, Barclay, Martikainen, & Myrskylä, 2017; Mohammed, Bonsing, Yakubu, & Wondong, 2019). The pattern of nursing care for newborns with appropriate LBW is proven to reduce infant mortality due to low birth weight. (Wanda, Rustina, Hayati, & Waluyanti, 2014). The role of practicing midwives should be to monitor the development of pregnant women during pregnancy. (Hüseyin, Muazzez, & Yadigar, 2020). On the other hand, the consumption of Fe tablets also had a significant effect on reducing stunting cases, especially for the mother who is experiencing Hb deficiency. (Figueiredo et al., 2018), (Lake & Olana Fite, 2019).

The frequency of pregnant women checking their pregnancy progress is crucial for the condition of the babies born. (Kusrini et al., 2021; Xi et al., 2020). By then, problems that occur in pregnant women, for example, a lack of nutritional intake or chronic lack of energy, can be immediately handled. (Nyamasege et al., 2019), (Hughes, Black, & Katz, 2017). Preferred pregnancy checks are during the first trimester. Protein and Fe consumption are the highest impact on preventing stunting in newborns.

The findings of this study have important implications for stunting prevention policies, particularly in coastal and high-prevalence areas of East Java. The symbolic regression model identified maternal nutritional status, iron supplementation, protein intake, paternal smoking behavior, and household health conditions as the most influential determinants of newborn stunting. Therefore, intervention programs should prioritize improving maternal nutrition during pregnancy through adequate consumption of animal protein, iron supplementation, and regular monitoring of maternal hemoglobin levels. Previous studies have demonstrated that maternal nutritional status and anemia during pregnancy are strongly associated with adverse birth outcomes and increased risk of growth failure in children (Figueiredo et al., 2018; Lake & Olana Fite, 2019). In addition, public health campaigns aimed at reducing paternal smoking behavior and improving household environmental health conditions may contribute to reducing stunting risk, particularly in vulnerable communities where environmental and socioeconomic factors play an important role in child growth and development (Vilcins et al., 2018; Flores-Quispe et al., 2019). These findings support the need for integrated maternal and child health programs that combine nutritional interventions, family health education, and community-based prevention strategies in vulnerable coastal communities.

Although the predictive performance of the proposed model was exceptionally high, particularly the 100% classification accuracy observed in the testing dataset, the possibility of overfitting should be considered. Genetic Programming is a highly flexible machine learning approach capable of capturing complex nonlinear relationships; however, such flexibility may also increase the risk of fitting patterns that are specific to a particular dataset. In this study, the model was developed using 600 training samples and evaluated on an independent testing set consisting of 50 samples. The high consistency between training and testing performance suggests strong predictive capability within the observed population. Nevertheless, because external validation data were not available, caution is required when generalizing the model to different populations or geographic regions. Future studies should incorporate additional validation procedures, such as k-fold cross-validation, bootstrapping techniques, or external validation using datasets from other provinces and coastal regions, to further assess model robustness and generalizability. Similar recommendations have been emphasized in previous predictive modeling studies, which highlight the importance of independent validation to ensure model reliability and applicability across different populations (Cooper et al., 2019; Takele et al., 2019).

Another limitation of this study is that the data were collected exclusively from selected districts in East Java Province with relatively high stunting prevalence. Consequently, the resulting model may reflect demographic, socioeconomic, environmental, and health characteristics that are specific to the study area. While the model provides valuable insights into the determinants of newborn stunting in East Java, its applicability to other regions with different population characteristics remains to be confirmed. Previous studies have reported substantial geographic and socioeconomic heterogeneity in stunting prevalence and determinants across regions and countries, suggesting that local contextual factors should be considered when applying predictive models to different populations (Restrepo-Méndez et al., 2015; Gatica-Domínguez et al., 2019). Future research involving larger and more diverse populations will be necessary to evaluate the broader applicability of the proposed symbolic regression model.

4. Conclusions

Based on the results of this study, building a model with a symbolic regression model approach produces a model with high accuracy. Independent variables that have a high contribution to the incidence of stunting include a history of respiratory disease, father smoker, maternal body mass index, maternal Hb level during pregnancy, iron consumption, consumption of vegetable protein, consumption of animal protein, and consumption of milk. The most dominant variable affecting the incidence of stunting is the consumption of animal protein, where the higher and sufficient consumption of animal protein during pregnancy, the smaller the chance of stunting in newborns.

Conflict of Interest Declaration

The authors have no conflicts of interest to declare. All co-authors have seen and agree with the contents of the manuscript, and there is no financial interest to report.

References

1. Aridiyah, F. O., Rohmawati, N., & Ririanty, M. (2015). Faktor-faktor yang Mempengaruhi Kejadian Stunting pada Anak Balita di Wilayah Pedesaan dan Perkotaan. *E-Jurnal Pustaka Kesehatan*, *3*(1), 163–170. https://doi.org/10.1007/s11746-013-2339-4
2. Bentian, Mayulu, N., & Rattu, A. J. M. (2015). Faktor Resiko Terjadinya Stunting pada Anak TK di Wilayah Kerja Puskesmas Siloam Tamako Kabupaten Sangihe Propinsi Sulawesi Utara. *Jikmu*, *5*(1), 1–7. Retrieved from http://download.portalgaruda.org/
3. Cooper, M. W., Brown, M. E., Hochrainer-Stigler, S., Pflug, G., McCallum, I., Fritz, S., … Zvoleff, A. (2019). Mapping the effects of drought on child stunting. *Proceedings of the National Academy of Sciences of the United States of America*. https://doi.org/10.1073/pnas.1905228116
4. Dinas Komunikasi dan Informatika Pemerintah Provinsi Jawa Timur. (2019). Selama Tahun 2019, Pemprov Jatim Fokus di 12 Kabupaten Tangani Masalah Stunting. Retrieved October 29, 2020, from http://kominfo.jatimprov.go.id/read/umum/selama-tahun-2019-pemprov-jatim-fokus-di-12-kabupaten-tangani-masalah-stunting
5. Figueiredo, A. C. M. G., Gomes-Filho, I. S., Silva, R. B., Pereira, P. P. S., Da Mata, F. A. F., Lyrio, A. O., … Pereira, M. G. (2018, May 12). Maternal anemia and low birth weight: A systematic review and meta-analysis. *Nutrients*. MDPI AG. https://doi.org/10.3390/nu10050601
6. Flores-Quispe, M. D. P., Restrepo-Méndez, M. C., Maia, M. F. S., Ferreira, L. Z., & Wehrmeister, F. C. (2019). Trends in socioeconomic inequalities in stunting prevalence in Latin America and the Caribbean countries: Differences between quintiles and deciles. *International Journal for Equity in Health*, *18*(1), 1–10. https://doi.org/10.1186/s12939-019-1046-7

7. Gatica-Domínguez, G., Victora, C., & Barros, A. J. D. (2019). Ethnic inequalities and trends in stunting prevalence among Guatemalan children: an analysis using national health surveys 1995-2014. *International Journal for Equity in Health*, *18*(1), 110. https://doi.org/10.1186/s12939-019-1016-0
8. Goisis, A., Remes, H., Barclay, K., Martikainen, P., & Myrskylä, M. (2017). Advanced Maternal Age and the Risk of Low Birth Weight and Preterm Delivery: A Within-Family Analysis Using Finnish Population Registers. *American Journal of Epidemiology*, *186*(11), 1219–1226. https://doi.org/10.1093/aje/kwx177
9. Hagos, S., Lunde, T., Mariam, D. H., Woldehanna, T., & Lindtjørn, B. (2014). Climate change, crop production, and child under nutrition in Ethiopia: A longitudinal panel study. *BMC Public Health*. https://doi.org/10.1186/1471-2458-14-884
10. Hughes, M. M., Black, R. E., & Katz, J. (2017). 2500-g Low Birth Weight Cutoff: History and Implications for Future Research and Policy. *Maternal and Child Health Journal*, *21*(2), 283–289. https://doi.org/10.1007/s10995-016-2131-9
11. Hüseyin, Ç. H., Muazzez, H., & Yadigar, P. (2020). A study of low birth weight prevalence and risk factors among newborns in a public-hospital at Kilis, Turkey. *African Health Sciences*, *20*(2), 709–714. https://doi.org/10.4314/ahs.v20i2.22
12. Ibrahim, R. (2014). Hubungan Pola Asuh Ibu Dengan Kejadian Stunting Anak Usia 24-59 Bulan Di Posyandu Asoka II Wilayah Pesisir Kelurahan Ba- rombong Kecamatan Tamalate Kota Makassar Tahun 2014. *Public Health Science Journal*. https://doi.org/10.9734/EJNFS/2015/20911
13. Khan, J., & Mohanty, S. K. (2018). Spatial heterogeneity and correlates of child malnutrition in districts of India. *BMC Public Health*. https://doi.org/10.1186/s12889-018-5873-z
14. Kusrini, I., Supadmi, S., Mulyantoro, D. K., & Laksono, A. D. (2021). Demographic characteristics of mother as predictor of low birth weight in eastern Indonesia. *Systematic Reviews in Pharmacy*, *12*(1), 1514–1518. https://doi.org/10.31838/srp.2021.1.213
15. Kusumawati, E., Rahardjo, S., & Sari, H. P. (2015). Model Pengendalian Faktor Risiko Stunting pada Anak Bawah Tiga Tahun. *Kesmas: National Public Health Journal*, *9*(3), 249. https://doi.org/10.21109/kesmas.v9i3.572
16. Lake, E. A., & Olana Fite, R. (2019). Low Birth Weight and Its Associated Factors among Newborns Delivered at Wolaita Sodo University Teaching and Referral Hospital, Southern Ethiopia, 2018. *International Journal of Pediatrics*, *2019*, 1–7. https://doi.org/10.1155/2019/4628301
17. Lestari, W., Margawati, A., & Rahfiludin, Z. (2014). Faktor risiko stunting pada anak umur 6-24 bulan di kecamatan Penanggalan kota Subulussalam provinsi Aceh. *Jurnal Gizi Indonesia (The Indonesian Journal of Nutrition)*, *3*(1), 37–45. https://doi.org/10.14710/jgi.3.1.126-134
18. Lloyd, S. J., Sari Kovats, R., & Chalabi, Z. (2011). Climate change, crop yields, and undernutrition: Development of a model to quantify the impact of climate scenarios on child undernutrition. *Environmental Health Perspectives*. https://doi.org/10.1289/ehp.1003311

19. Mohammed, S., Bonsing, I., Yakubu, I., & Wondong, W. P. (2019). Maternal obstetric and socio-demographic determinants of low birth weight: A retrospective cross-sectional study in Ghana. *Reproductive Health*, *16*(1). https://doi.org/10.1186/s12978-019-0742-5
20. Nguyen, T. huong. (2014). *Birth weight and growth during the first two years of life : a study in urban and rural Vietnam*. Nordic School of Public Health NHV.
21. Nyamasege, C. K., Kimani-Murage, E. W., Wanjohi, M., Kaindi, D. W. M., Ma, E., Fukushige, M., & Wagatsuma, Y. (2019). Determinants of low birth weight in the context of maternal nutrition education in urban informal settlements, Kenya. *Journal of Developmental Origins of Health and Disease*, *10*(2), 237–245. https://doi.org/10.1017/S2040174418000715
22. Olsa, E. D., Sulastri, D., & Anas, E. (2018). Hubungan Sikap dan Pengetahuan Ibu Terhadap Kejadian Stunting pada Anak Baru Masuk Sekolah Dasar di Kecamanatan Nanggalo. *Jurnal Kesehatan Andalas*.
23. Renyoet, B. S., Hadju, V., & Rochimiwati, S. N. (2013). HUBUNGAN POLA ASUH DENGAN KEJADIAN STUNTING ANAK USIA 6-23 BULAN DI WILAYAH PESISIR KECAMATAN TALLO KOTA MAKASSAR. *Program Studi Ilmu Gizi Fakultas Kesehatan Masyarakat Universitas Hasanuddin Makassar 2 Jurusan Gizi Politeknik Kesehatan Kemenkes Makassar*. https://doi.org/10.1017/S146342361200031X
24. Restrepo-Méndez, M. C., Barros, A. J. D., Black, R. E., & Victora, C. G. (2015). Time trends in socio-economic inequalities in stunting prevalence: Analyses of repeated national surveys. *Public Health Nutrition*, *18*(12), 2097–2104. https://doi.org/10.1017/S1368980014002924
25. Rochmah, A. M. (2017). Faktor-Faktor Yang Berhubungan Dengan Stunting Pada Balita Usia 24-59 Bulan Di Wilayah Kerja Puskesmas Wonosari I. *Kebidanan*, 1–13.
26. Ryandi, D. (2020). Indonesia Urutan ke-4 Dunia, DPR Ingatkan Pemerintah Soal Stunting. *Jawa Pos*. Retrieved from https://www.jawapos.com/nasional/politik/23/06/2020/indonesia-urutan-ke-4-dunia-dpr-ingatkan-pemerintah-soal-stunting/
27. Said-Mohamed, R., Micklesfield, L. K., Pettifor, J. M., & Norris, S. A. (2015). Has the prevalence of stunting in South African children changed in 40 years? A systematic review. *BMC Public Health*, *15*(1), 1–10. https://doi.org/10.1186/s12889-015-1844-9
28. Setiawan, E., Machmud, R., & Masrul, M. (2018). Faktor-Faktor yang Berhubungan dengan Kejadian Stunting pada Anak Usia 24-59 Bulan di Wilayah Kerja Puskesmas Andalas Kecamatan Padang Timur Kota Padang Tahun 2018. *Jurnal Kesehatan Andalas*, *7*(2), 275. https://doi.org/10.25077/jka.v7i2.813
29. Sulastri, D. (2012). Faktor Determinan Kejadian Stunting Pada Anak Usia Sekolah Di Kecamatan Lubuk Kilangan Kota Padang. *Majalah Kedokteran Andalas*, *36*(1), 39. https://doi.org/10.22338/mka.v36.i1.p39-50.2012
30. Takele, K., Zewotir, T., & Ndanguza, D. (2019). Understanding correlates of child stunting in Ethiopia using generalized linear mixed models. *BMC Public Health*. https://doi.org/10.1186/s12889-019-6984-x
31. Vilcins, D., Sly, P. D., & Jagals, P. (2018). Environmental risk factors associated with child stunting: A systematic review of the literature. *Annals of Global Health*. https://doi.org/10.29024/aogh.2361

32. Wahdah, S., Juffrie, M., & Huriyati, E. (2016). Faktor risiko kejadian stunting pada anak umur 6-36 bulan di Wilayah Pedalaman Kecamatan Silat Hulu, Kapuas Hulu, Kalimantan Barat. *Jurnal Gizi Dan Dietetik Indonesia (Indonesian Journal of Nutrition and Dietetics)*. https://doi.org/10.21927/ijnd.2015.3(2).119-130
33. Wanda, D., Rustina, Y., Hayati, H., & Waluyanti, F. T. (2014). Pengembangan model pelayanan asuhan keperawatan bayi berat lahir rendah. *Jurnal Ners*, *9*(1), 83–90.
34. Wellina, W. F., Kartasurya, M. I., & Rahfilludin, M. Z. (2016). Faktor risiko stunting pada anak usia 6 - 12 bulan. *Jurnal Gizi Indonesia*, *5*(1), 55–61.
35. Wessells, K. R., & Brown, K. H. (2012). Estimating the Global Prevalence of Zinc Deficiency: Results Based on Zinc Availability in National Food Supplies and the Prevalence of Stunting. *PLoS ONE*, *7*(11). https://doi.org/10.1371/journal.pone.0050568
36. Xi, C., Luo, M., Wang, T., Wang, Y., Wang, S., Guo, L., & Lu, C. (2020). Association between maternal lifestyle factors and low birth weight in preterm and term births: A case-control study. *Reproductive Health*, *17*(1). https://doi.org/10.1186/s12978-020-00932-9