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## **STUNTING DETERMINANTS AMONG TODDLERS IN PROBOLINGGO DISTRICT OF INDONESIA USING PARAMETRIC AND NONPARAMETRIC ORDINAL LOGISTIC REGRESSION MODELS**

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**Abstract:** Stunting is a chronic nutritional problem in toddlers characterized by a shorter height than other children of their age. Stunting is a major nutritional problem faced by Indonesia. This research aimed to develop a risk model for the incidence of stunting in toddlers. This research was conducted in the village of stunting locus in the Public Health Center area that was selected to be the sample in Probolinggo District. Data were collected in the villages of Alaspandan, Bucorwetan, Petunjungan, and Sukodadi. The samples taken were 202 toddlers. The results show that the prevalence of a stunted toddler was 26.7% consisting of 21.3% moderately stunting and 5.4% severely stunting, and birth length, maternal height, and health services were important determinants of stunting in toddlers. Also, the

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value of the classification accuracy of the obtained model using parametric ordinal logistic regression approach was 72.45% which is less than that using nonparametric ordinal logistic regression approach namely 73.98%. It means that the best model for modeling risk of toddlers stunting in Probolinggo District was obtained based on the nonparametric logistic regression approach.

**Keywords:** ordinal logistic; nonparametric; nutritional status; stunting.

**2020 AMS Subject Classification:** 62F10, 62G05, 62G08.

## 1. INTRODUCTION

One of the strategic issues that becomes a priority in health development in Indonesia which resulted in the 2019 National Health Working Meeting is stunting. Stunting is a chronic nutritional problem in toddlers, characterized by a shorter height than other children their age. Although the 2018 Basic Health Research stated a decrease in the stunting rate from 37.2% (in 2013) to 30.8% (in 2017), this figure is still higher than the maximum stunting rate set by WHO, which is 20%. The government must seriously deal with stunting because it can reduce the productivity of human resources of Indonesia in the future. It is important to reduce the incidence of stunting in toddlers as early as possible to avoid long-term adverse impacts such as stunted child development. Stunting can affect brain development so that the child's intelligence level is not optimal. This is at risk of reducing productivity as an adult. Stunting also makes children more susceptible to disease. Children who are stunted have a higher risk of developing chronic diseases in adulthood [1].

There are two approaches in the regression modeling namely parametric regression and nonparametric regression approaches [2]. The parametric regression known as global approach assumes that the regression model for each observation has the same parameters, while the nonparametric regression known as local approach assumes that not all observations have the same parameters [3]. Next, related to children growth, the children born up to about one year of age have physical growth that increases rapidly and then decreases slowly as the child gets older [4].

Therefore, the nonparametric regression model approach locally was applied to this type of data pattern [5].

There are many researchers who have discussed not only parametric regression but also nonparametric regression using some estimators [6–15]. Also, several researches examining the factors which are influence the incidence of stunting in toddlers have been carried out parametrically by [16–19]. This study aimed to develop a risk model for the incidence of stunting in a toddler using parametric and nonparametric ordinal logistic regressions approaches and then the best model will be obtained.

## **2. PRELIMINARIES**

In this section, we provide brief overview of dataset's description, parametric ordinal logistic regression model, and nonparametric ordinal logistic regression model.

### **2.1. Dataset**

The data used in this research were data on toddlers nutritional status provided in the applications of *Aplikasi Satu Posyandu* (ASP) and *Aplikasi Posyandu Rekap* (APR) that were obtained from the Public Health Center, as well as survey data on mothers of toddlers who were selected as research samples. Based on the cluster sampling technique, this research was conducted in the villages of stunting locus in the Public Health Center area that was selected as the sample namely Public Health Center of Glagah and Public Health Center of Paiton in Probolinggo District of Indonesia. Data collection were carried out by village midwives and assisted by integrated health care center cadres in the villages selected as research samples, which are Alaspandan, Bucorwetan, Petunjungan, and Sukodadi. The samples were 202 toddlers consisting of 80 toddlers from Alaspandan and Bucorwetan villages (Public Health Center of Glagah area) and 122 toddlers from Petunjungan and Sukodadi villages (Public Health Center of Paiton area). Data collection were carried out during the weighing month of August 2020, one of the government's programs to provide comprehensive information on nutritional status data for toddlers.

## 2.2. Parametric Ordinal Logistic Regression Model

Parametric logistic regression models are used to model the relationship between categorical response variables and predictor variables which are categorical or continuous. If the response variable consists of two categories, it is called a dichotomous or binary logistic regression model. Next, if the response variable is divided into more than two categories, it is called a polycotomous logistic regression model, and if there is a level in which category (ordinal scale), it is called an ordinal logistic regression model [20].

Models that can be used for ordinal logistic regression are cumulative logit models. Suppose the response variable  $Y$  has as many as  $G$  categories on the ordinal scale, and  $\mathbf{x}_i$  represents the vector of the predictor variable in the  $i^{th}$  observation,  $\mathbf{x}_i = [x_{i1} \ x_{i2} \ \dots \ x_{ip}]^T$  for  $i = 1, 2, \dots, n$ , then the cumulative logit model can be presented as follows:

$$(1) \quad \text{logit} \left[ P(Y_i \leq g | \mathbf{x}_i) \right] = \alpha_g + \mathbf{x}_i^T \boldsymbol{\beta}$$

where  $g = 1, 2, \dots, G-1$ ;  $P(Y_i \leq g | \mathbf{x}_i)$  is the cumulative probability of being less than or equal to category  $g$  against  $\mathbf{x}_i$ ;  $\{\alpha_g\}$  represents intercepts and meet the conditions  $\alpha_1 \leq \alpha_2 \leq \dots \leq \alpha_{G-1}$ ; and  $\boldsymbol{\beta} = [\beta_1 \ \beta_2 \ \dots \ \beta_p]^T$  is the vector of the regression coefficients corresponding to  $x_1, x_2, \dots, x_p$ . The cumulative logit is also defined as follows:

$$(2) \quad \text{logit} \left[ P(Y_i \leq g | \mathbf{x}_i) \right] = \ln \left[ \frac{P(Y_i \leq g | \mathbf{x}_i)}{1 - P(Y_i \leq g | \mathbf{x}_i)} \right]$$

Based on Eq.(1) and Eq.(2), the ordinal logistic regression model can be presented as follows:

$$(3) \quad \ln \left[ \frac{P(Y_i \leq g | \mathbf{x}_i)}{1 - P(Y_i \leq g | \mathbf{x}_i)} \right] = \alpha_g + \mathbf{x}_i^T \boldsymbol{\beta}$$

Hence, we have:

$$(4) \quad P(Y_i \leq g | \mathbf{x}_i) = \frac{\exp(\alpha_g + \mathbf{x}_i^T \boldsymbol{\beta})}{1 + \exp(\alpha_g + \mathbf{x}_i^T \boldsymbol{\beta})}$$

Next, suppose  $\pi_g(\mathbf{x}_i) = P(Y_i = g | \mathbf{x}_i)$  represents the probability of response variable in the  $i^{th}$

observation which has the category  $g$  against  $\mathbf{x}_i$ . Thus, the probability of each response category can be expressed as follows:

$$(5) \quad \pi_g(\mathbf{x}_i) = P(Y_i \leq g | \mathbf{x}_i) - P(Y_i \leq g-1 | \mathbf{x}_i)$$

The probability score for each response category is used as a guide for classification. An observation will be included in the response category  $g$  based on the greatest probability value. Estimator for parameters of ordinal logistic regression model can be obtained using the maximum likelihood estimation (MLE) method. The principle of the MLE method is to estimate parameters by maximizing the likelihood function which is obtained by taking the first partial derivative of the likelihood function with respect to its parameters, and then and then it equates to zero. The result of this process is a non-linear function of the parameters to be estimated. Therefore, a numerical method is needed to obtain the parameters estimates. The numerical method that can be used is the Newton-Raphson iteration method.

### 2.3. Nonparametric Ordinal Logistic Regression Model

The nonparametric ordinal logistic regression model is a development model of the ordinal logistic regression model using nonparametric regression approach. According to [21], the general form of nonparametric ordinal logistic regression model is as follows:

$$(6) \quad \text{logit} \left[ P(Y_i \leq g | \mathbf{x}_i) \right] = \alpha_g + \sum_{j=1}^p f_j(x_j)$$

where  $\mathbf{x} = [1 \ x_1 \ x_2 \ \dots \ x_p]^T$  is a vector of the predictor variable;  $\alpha$  is the intercept; and  $f_j(\cdot)$  is unknown regression function of the  $j^{\text{th}}$  predictor variable which will be estimated using nonparametric regression approach based on local linear estimator.

According to [22], if  $x_j$  is being in the area of  $x_{0j}$  then the function  $f_j(\cdot)$  will be approached by Taylor's expansion to  $d = 1$  which can be presented as follows:

$$(7) \quad f_j(x_j) \approx f_j(x_{0j}) + (x - x_{0j})f'_j(x_{0j}) \equiv \beta_0(x_{0j}) + \beta_1(x_{0j})(x_j - x_{0j})$$

Based on Eq.(7), the Eq.(6) can be expressed as follows:

$$\begin{aligned}
(8) \quad \text{logit} \left[ P(Y \leq g | \mathbf{x}) \right] &= \alpha_g + \sum_{j=1}^p \left[ \beta_0(x_{0j}) + \beta_1(x_{0j})(x_j - x_{0j}) \right] \\
&= \alpha_g + \beta_0(x_{01}) + \beta_1(x_{01})(x_1 - x_{01}) + \dots + \beta_0(x_{0p}) + \beta_1(x_{0p})(x_p - x_{0p}) \\
&= \alpha_g + \beta_0(x_0) + \beta_1(x_{01})(x_1 - x_{01}) + \dots + \beta_1(x_{0p})(x_p - x_{0p}) \\
&= \alpha_g + \tilde{\mathbf{x}}^T(x_0) \boldsymbol{\beta}(x_0)
\end{aligned}$$

where  $\boldsymbol{\beta}(x_0) = [\beta_0 \quad \beta_1(x_{01}) \quad \beta_2(x_{02}) \quad \dots \quad \beta_p(x_{0p})]^T$  and

$$\tilde{\mathbf{x}}(x_0) = [1 \quad x_1 - x_{01} \quad x_2 - x_{02} \quad \dots \quad x_p - x_{0p}]^T$$

Based on Eq.(6) and Eq.(8), the cumulative probability of the response category  $g$  can be expressed as follows:

$$(9) \quad P(Y \leq g | \mathbf{x}) = \frac{\exp(\alpha_g + \tilde{\mathbf{x}}^T(x_0) \boldsymbol{\beta}(x_0))}{1 + \exp(\alpha_g + \tilde{\mathbf{x}}^T(x_0) \boldsymbol{\beta}(x_0))}$$

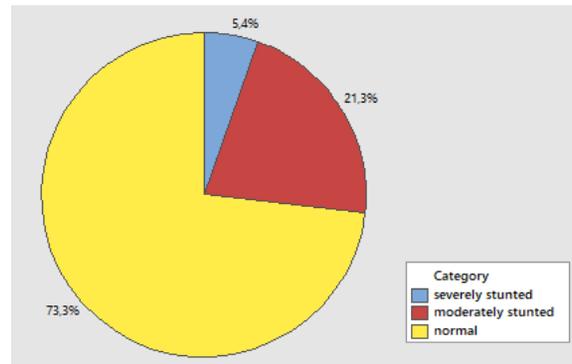
The estimation of parameters of nonparametric ordinal logistic regression model was carried out using local maximum likelihood estimation (LMLE) method. The results of the first partial derivatives obtained are implicit form, thus a numerical method is needed to obtain the parameters estimations. The numerical method that can be used is the Newton-Raphson iteration method [2].

### 3. MAIN RESULTS

The response variable ( $Y$ ) used in this research was the nutritional status of toddlers based on the height/age index which was categorized into three categories namely severely stunted ( $Y = 1$ ), moderately stunted ( $Y = 2$ ), and normal ( $Y = 3$ ). Meanwhile, the predictor variable ( $X$ ) consists of 11 continuous variables namely birth weight ( $X_1$ ), birth length ( $X_2$ ), parity ( $X_3$ ), maternal age ( $X_4$ ), maternal height ( $X_5$ ), maternal knowledge of nutrition ( $X_6$ ), parenting pattern ( $X_7$ ), health services ( $X_8$ ), hygiene and sanitation ( $X_9$ ), number of children ( $X_{10}$ ), and number of family members ( $X_{11}$ ).

### 3.1. Characteristics of Research Variables

The characteristic analysis of research variables describes the condition of the toddlers who were used as samples of the research. The characteristic analysis for the response variable is presented in Fig.1.



**Figure 1.** Percentage of nutritional status of toddler based on the index height/age

Based on Fig.1, it can be seen that the prevalence of toddlers who experience stunting is 26.7%, consisting of 21.3% moderately stunting and 5.4% severely stunting. Furthermore, based on the characteristic analysis of the predictor variables, it can be seen that the variable of birth weight has an average of 3.019 kg, but at its minimum value, there is still birth weight which is less than 2 kg, namely 1.6 kg. It shows that there are still toddlers who were born prematurely. Furthermore, the variable of maternal age has a median value of 30 years, but the minimum and maximum ages of 20 years and 43 years are the period outside the age of the mother to give birth to healthy babies. So, there is a possibility that toddlers were born less healthy, and in other variables the parenting pattern has a median value of 80 and a minimum value of 20. This proves that there is still lack of maximal application of good parenting styles for toddlers. Also, the variable of hygiene and sanitation has median value of 60 and minimum value of 0. This indicates that there is still lack of implementation of cleanliness and sanitation in the environment where toddlers live.

Before analyzing the data using regression, data exploration was carried out for each predictor variable using the boxplot to detect any outliers. Based on the boxplot output, there are six observations detected to have outlier data, i.e. variable of birth weight in the 44<sup>th</sup> observation, variable of birth length in the 49<sup>th</sup> and 100<sup>th</sup> observations, and the number of family members

in the 52, 71, and 85 observations. Therefore, the six outliers were excluded from the research data for further analysis. Thus, the number of research data used for further analysis were 196 observations.

Furthermore, multicollinearity detection is carried out to determine whether there is a linear relationship between predictor variables in ordinal logistic regression. The existence of multicollinearity cases can be investigated based on the VIF value with a limit of 10. Based on the results of multicollinearity detection of the research data, it was found that the variable of parity ( $X_3$ ) and number of children ( $X_{10}$ ) had VIF values more than 10. So it can be said that the two variables experienced multicollinearity cases. Therefore, those variables are excluded from the model. Thus, for further analysis, 9 predictor variables were used.

### 3.2. Modeling the Risk of Toddlers Stunting in District of Probolinggo Based on Parametric Ordinal Logistic Regression

The first step to build the risk model for the incidence of stunting in a toddler in Probolinggo District was carried out using the parametric logistic regression approach. Based on the results of testing the parameters simultaneously, we obtained a Chi-square value of 36.655 and a p-value of 0.000. It can be concluded that there are predictor variables that have a significant effect on the model simultaneously. Furthermore, a partial test is carried out to detect what predictor variables are influencing the model. Based on the results of partial parameter testing, the following outputs are obtained :

**TABLE 1.** Ordinal logistic regression partial test

Parameter	Estimate	Std. Error	Wald	Sig.
[Y = 1]	33.832	8.397	16.234	.000
[Y = 2]	35.932	8.445	18.101	.000
$\beta_1$	.559	.577	.939	.333
$\beta_2$	-.434	.143	9.263	<b>.002</b>
$\beta_4$	.018	.034	.292	.589

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Parameter	Estimate	Std. Error	Wald	Sig.
$\beta_5$	-.106	.036	8.481	<b>.004</b>
$\beta_6$	.007	.012	.311	.577
$\beta_7$	-.009	.009	1.137	.286
$\beta_8$	-.017	.010	3.004	<b>.083</b>
$\beta_9$	-.000	.010	.000	.999
$\beta_{11}$	.016	.148	.012	.914

Based on Table 1, it can be seen that three variables have significance values below the 10% significance level, i.e. 0.002, 0.004, and 0.083 which are owned by the variables  $X_2$  (Birth Length),  $X_5$  (Maternal Height), and  $X_8$  (Health Services). Furthermore, the ordinal logistic regression model is built from significantly influential variables. Variable selection was carried out by backward eliminations, where insignificant variables were excluded from the model and carried out re-ordinal logistic regression testing with the variables used in the model were birth length, maternal height, and health services. The results of simultaneously parameters testing after the backward eliminations method showed that there were predictor variables that significantly affected the model. Furthermore, a partial test is carried out and its outputs are given in Table 2.

**TABLE 2.** Ordinal logistic regression partial test after the backward eliminations method was Applied.

Parameter	Estimate	Std. Error	Wald	Sig.
[Y = 1]	33.193	7.115	21.763	.000
[Y = 2]	35.252	7.170	24.171	.000
$\beta_2$	-.385	.105	13.290	.000
$\beta_5$	-.104	.035	9.128	.003
$\beta_8$	-.018	.009	3.545	.060

Table 2 shows that birth length, maternal height, and health services have a significant effect

at the 10% significance level, so that these three variables determine the risk of stunting in infants based on parametric ordinal logistic regression model. These models are as follows:

$$\text{logit} \left[ \hat{P}(Y_i \leq 1 | x_i) \right] = 33.193 - 0.385X_2 - 0.104X_5 - 0.018X_8$$

$$\text{logit} \left[ \hat{P}(Y_i \leq 2 | x_i) \right] = 35.252 - 0.385X_2 - 0.104X_5 - 0.018X_8$$

Furthermore, the probability function of each response category can be obtained as follows:

(i). The probability of the nutritional status of toddlers who are severely stunted is given by:

$$\pi_1(\mathbf{x}) = \frac{\exp(33.193 - 0.385X_2 - 0.104X_5 - 0.018X_8)}{1 + \exp(33.193 - 0.385X_2 - 0.104X_5 - 0.018X_8)}$$

(ii). The probability of nutritional status of toddlers who are moderately stunted is given by:

$$\pi_2(\mathbf{x}) = \frac{\exp(35.252 - 0.385X_2 - 0.104X_5 - 0.018X_8)}{1 + \exp(35.252 - 0.385X_2 - 0.104X_5 - 0.018X_8)} - \frac{\exp(33.193 - 0.385X_2 - 0.104X_5 - 0.018X_8)}{1 + \exp(33.193 - 0.385X_2 - 0.104X_5 - 0.018X_8)}$$

(iii). The probability of nutritional status of toddlers who are normal is given by:

$$\pi_3(\mathbf{x}) = 1 - \frac{\exp(35.252 - 0.385X_2 - 0.104X_5 - 0.018X_8)}{1 + \exp(35.252 - 0.385X_2 - 0.104X_5 - 0.018X_8)}$$

The next step is testing suitability of the model to find out whether the model equation that has been formed is appropriate. The result of the model suitability test shows that the P-value for Deviance is 1 so that the model obtained is suitable. The final step is calculating the value of the classification accuracy between the actual value and the predicted value obtained from the model that has been built. The result of the classification accuracy of the risk modeling of the incidence of child stunting in Probolinggo district using the parametric ordinal logistic regression approach was 72.45%.

### **3.3. Modeling the risk of Toddlers Stunting in District of Probolinggo Based on Nonparametric Ordinal Logistic Regression**

The first step to obtain parameter estimation of nonparametric ordinal logistic regression model using local maximum likelihood estimation method is by determining the optimal bandwidth for

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each predictor variable, which is the bandwidth that has a minimum CV value. The optimal bandwidth results for each significant predictor variable, i.e. birth length, maternal height, and health services were 4.34, 8.84, and 50.01, respectively, with CV values of 39.08.

Furthermore, these optimal bandwidths are used to estimate the parameters for each observation with fixed point arbitrary. The results of parameters estimation for each observation are presented in Table 3.

**TABLE 3.** Result of parameter estimation for each observation

Toddler	$X_2$	$X_5$	$X_8$	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\beta}_2(x_0)$	$\hat{\beta}_5(x_0)$	$\hat{\beta}_8(x_0)$
1	48,00	149,0	75	33.1474	35.2974	-0.4073	-0.0992	-0.0140
2	49,00	152,5	100	33.1666	35.2783	-0.3977	-0.1020	-0.0144
3	50,00	153,5	100	33.1913	35.2537	-0.3910	-0.1031	-0.0161
4	51,00	153,0	75	33.2548	35.1903	-0.3845	-0.1030	-0.0193
5	48,00	155,0	75	33.2302	35.2149	-0.3778	-0.1063	-0.0177
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

The estimation results of these parameters are used for estimating the probability of each toddler who suffers from stunting. Furthermore, the classification accuracy value obtained from modeling the risk of stunting incidence of children under five in Probolinggo District using a nonparametric ordinal logistic regression approach was 73.98%.

### 3.4. Determination of the Best Model

In summary, the comparison of the classification accuracy values of modeling the risk of stunting in toddlers under five based on the parametric and nonparametric regression approaches is presented in Table 4.

**TABLE 4.** Comparison of classification accuracy values

Model	Classification Accuracy
Parametric ordinal logistic regression	72.45%
Nonparametric ordinal logistic regression	73.98%

Based on the validation results in Table 4, it can be seen that the best model for modeling the risk of stunting in toddlers under five in Probolinggo District is model obtained based on a nonparametric ordinal logistic regression approach with classification accuracy of 73.98%. This shows that the nonparametric ordinal logistic regression approach has improved the classification accuracy although the increase is not very significant.

#### **4. CONCLUSIONS**

Based on the analysis of variable characteristics, it shows that the prevalence of toddlers under five who are stunted is 26.7%, consisting of 21.3% moderately stunted and 5.4% severely stunted. Based on the parametric ordinal logistic regression model approach, three variables significantly influence stunting in toddlers under five, i.e. birth length, maternal height, and health services. The classification accuracy value of the parametric ordinal logistic regression model was 72.45%. Furthermore, nonparametric ordinal logistic regression modeling was carried out and an increase in the classification accuracy value was 73.98%. Thus, the best model for modeling the risk of stunting in toddlers under five in District of Probolinggo is obtained based on the nonparametric ordinal logistic regression approach.

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#### **CONFLICT OF INTERESTS**

The authors declare that there is no conflict of interests.

**REFERENCES**

- [1] Pusdatin-Kemenkes, The situation of stunting in Indonesia, Health Data and Information Window Bulletin: Semester 1, Ministry of Health of the Republic of Indonesia, Jakarta, (2018).
- [2] M. Rifada, N. Chamidah, V. Ratnasari, et al. Estimation of nonparametric ordinal logistic regression model using local maximum likelihood estimation, *Commun. Math. Biol. Neurosci.* 2021 (2021), 28.  
<https://doi.org/10.28919/cmbn/5353>.
- [3] M. Rifada, Suliyanto, E. Tjahjono, et al. The logistic regression analysis with nonparametric approach based on local scoring algorithm (Case study: Diabetes mellitus type II cases in Surabaya of Indonesia), *Int. J. Adv. Soft Comput. Appl.* 10 (2018), 167-178.
- [4] M.B. Narendra, T.S. Sularyo, Soetjningsih, et al. Growth and development of children and adolescents, CV Sagung Seto, Jakarta, (2002).
- [5] N. Chamidah, M. Rifada, Estimation of median growth curves for children up two years old based on biresponse local linear estimator, *AIP Conf. Proc.* 1718 (2016), 110001. <https://doi.org/10.1063/1.4943348>.
- [6] N. Chamidah, E. Tjahjono, A.R. Fadilah, et al. Standard growth charts for weight of children in East Java using local linear estimator, *J. Phys.: Conf. Ser.* 1097 (2018), 012092. <https://doi.org/10.1088/1742-6596/1097/1/012092>.
- [7] E. Ana, N. Chamidah, P. Andriani, B. Lestari, Modeling of hypertension risk factors using local linear of additive nonparametric logistic regression, *J. Phys.: Conf. Ser.* 1397 (2019), 012067. <https://doi.org/10.1088/1742-6596/1397/1/012067>.
- [8] N. Chamidah, Y.S. Yonani, E. Ana, B. Lestari, Identification the number of Mycobacterium tuberculosis based on sputum image using local linear estimator, *Bull. Electric. Eng. Inform.* 9 (2020), 2109–2116.  
<https://doi.org/10.11591/eei.v9i5.2021>.
- [9] N. Chamidah, K.H. Gusti, E. Tjahjono, et al. Improving of classification accuracy of cyst and tumor using local polynomial estimator, *Telkomnika.* 17 (2019), 1492-1500. <https://doi.org/10.12928/telkomnika.v17i3.12240>.
- [10] N. Chamidah, B. Lestari, Estimation of covariance matrix using multi-response local polynomial estimator for designing children growth charts: A theoretically discussion, *J. Phys.: Conf. Ser.* 1397 (2019), 012072.  
<https://doi.org/10.1088/1742-6596/1397/1/012072>.

- [11] N. Chamidah, B. Lestari, T. Saifudin, Modeling of blood pressures based on stress score using least square spline estimator in bi-response nonparametric regression, *Int. J. Innov. Creativity Change*. 5 (2019), 1200–1216.
- [12] B. Lestari, Fatmawati, I.N. Budiantara, et al. Estimation of regression function in multi-response nonparametric regression model using smoothing spline and kernel estimators, *J. Phys.: Conf. Ser.* 1097 (2018), 012091. <https://doi.org/10.1088/1742-6596/1097/1/012091>.
- [13] B. Lestari, Fatmawati, I.N. Budiantara, et al. Smoothing parameter selection method for multiresponse nonparametric regression model using smoothing spline and Kernel estimators approaches, *J. Phys.: Conf. Ser.* 1397 (2019), 012064. <https://doi.org/10.1088/1742-6596/1397/1/012064>.
- [14] Fatmawati, I.N. Budiantara, B. Lestari, Comparison of smoothing and truncated spline estimators in estimating blood pressures models, *Int. J. Innov. Creativity Change*. 5 (2019), 1177–1199.
- [15] B. Lestari, Fatmawati, I.N. Budiantara, Spline estimator and its asymptotic properties in multiresponse nonparametric regression model, *Songklanakarin J. Sci. Technol.* 42 (2020), 533–548.
- [16] M. Rifada, N. Chamidah, P. Nuraini, et al. Determinants of stunting among under-five years children using the ordinal logistic regression model, in: *Proceedings of the 1st International Conference on Mathematics and Mathematics Education (ICMMEd 2020)*. <https://doi.org/10.2991/assehr.k.210508.096>.
- [17] K. Ni'mah, S.R. Nadhiroh, Factors associated with stunting incidents in toddlers, *Media Gizi Indonesia*. 10 (2015), 13–19.
- [18] R. Paudel, B. Pradhan, R. Wagle, et al. Risk factors for stunting among children: A community based case control study in Nepal, *Kathmandu Univ. Med. J.* 10 (2013), 18–24. <https://doi.org/10.3126/kumj.v10i3.8012>.
- [19] F. Meilyasari, M. Isnawati, Risk factors of stunting in children aged 12 months in Purwokerto village, Patebon district, Kendal district, *J. Nutrition College*. 3 (2014), 16–25. <https://doi.org/10.14710/jnc.v3i2.5437>.
- [20] A. Agresti, *Categorical data analysis*, John Wiley & Sons, New Jersey, (2002).
- [21] T. Hastie, R. Tibshirani, Non-parametric logistic and proportional odds regression, *Appl. Stat.* 36 (1987), 260-276. <https://doi.org/10.2307/2347785>.
- [22] J. Fan, I. Gijbels, *Local polynomial modelling and its applications*, 1st ed. Chapman & Hall, London, (1996).