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Modelling the Number of Stunting Under-Five Children in East Nusa Tenggara Using Negative Binomial Regression

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Abstract

Malnutrition is an imbalance in a person's energy intake or nutrition. Stunting is one of the nutritional problems in toddlers, where stunting is a condition of growth failure in children under five caused by malnutrition. In Indonesia, East Nusa Tenggara Province has the highest number of toddlers with stunting cases. Therefore, efforts are needed to reduce the number of stunting, especially in East Nusa Tenggara. Several factors are thought to be closely related to the high number of stunting in toddlers. This study aims to find factors that can significantly explain stunting in East Nusa Tenggara to help accelerate the decrease in the number of stunting. This study will explore stunting data from the Ministry of Home Affairs in 2021 for data on East Nusa Tenggara and the Central Statistics Agency of East Nusa Tenggara Province. The appropriate modelling for the number of stunting is the Poisson regression model because the number of stunting is in the form of count data. The proper modelling for stunting cases in toddlers is the Poisson regression model because stunting cases in toddlers are in the form of count data. There is an overdispersion problem to overcome overdispersion in the Poisson regression model; a more suitable Poisson regression model is used as an alternative model. Furthermore, the Maximum Likelihood Estimation (MLE) method estimates the model's parameters. The results showed that the complete immunization variable, pregnant women get nutritional counselling variable, the variable low birth weight babies and the variable of families with beneficiary status had a significant effect on the number of stunting in East Nusa Tenggara.

Keywords: ***Overdispersion, Poisson Regression, Maximum Likelihood Estimation, Nutritional Deficiencies.***

1. INTRODUCTION

When discussing global health problems centred on toddlers, stunting is one of them. Stunting is a nutritional problem in around 149.2 million toddlers worldwide Unicef, (2020). WHO in 2020 stated that on the Asian continent, stunting ranks second among other continents with a prevalence of 30.10%, and Indonesia ranks second among countries on the Asian continent with a prevalence of 27.7% in 2019 World Health Organization, (2021). Moreover, based on data on Indonesia's nutritional status, the stunting prevalence rate has decreased compared to 2018 (30.8%) and 2013 (37.2%) .

Stunting is a disorder in which children under five fail to thrive due to chronic malnutrition, which makes children too short for their age. According to the 2020 Republic of Indonesia Minister of Health Regulation concerning Anthropometric standards for assessing the nutritional status of children, a toddler is said to be stunted if the threshold value (z-score) is -3 SD to less than -2 SD and is categorised as very short if the z-score is less of -3 SD of index length or height for age, Permenkes RI, (2020).

According to WHO, a public health problem can be classified as acute if stunting is more than 20 percent. It means that nationally, the problem of stunting in Indonesia is classified as acute, where based on the 2021 Toddler Nutrition Status Survey results, stunting has reached 24.4%. Children who experience stunting have an impact on stunted growth and are irreversible. The stunting effect can last a lifetime and affect the next generation. World Health Organization (2021). Stunting can occur in the first 1000 days of conception (until the child reaches two years of age) and is related to many factors, such as malnutrition. Malnutrition at an early age causes an unavoidable death rate of around one million children annually (Aguayo et al, 2018). Malnutrition can cause frequent illness in children who suffer from it and lousy posture when they are adults (Bloem et al. 2013). Other adverse impacts include decreased endurance, decreased cognitive ability, which results in poor learning quality, and susceptibilities to disease, such as cancer, stroke, and heart disease, which, when adults, can affect the quality of work (Aguayo et al, 2018), (Bloem et al. 2013).

The United Nations has worked to improve global nutrition achievements in the 2016-2025 Nutrition Decade(Hossain,et al 2013). That is in line with the multidimensional efforts to prevent and overcome stunting and accelerate the decline in prevalence proclaimed by the Indonesian government. Reducing the stunting rate can significantly change the country's socioeconomic conditions (Islam, et al. 2016).

Despite attempts to diminish stunting, as of 2021, there remain 20 provinces that have a stunting rate surpassing the national average of 24.4%. The province with the highest stunting rate is East Nusa Tenggara, with a prevalence of 37.8%. Thus, it becomes crucial to recognize the factors responsible for reducing the prevalence of stunting to a significant level.

This research study aims to identify the significant factors contributing to reducing stunting rates. In order to accomplish this, the method is required, and regression analysis serves as a helpful tool for prediction. It provides an understanding of the relationship between variables, allowing us to determine the impact of one variable on the other. While this type of analysis can handle discrete data variables, the Poisson regression model can be employed for analyzing the relationship between dependent variables in discrete data and independent variables. The Poisson regression model is a Generalized Linear Model (GLM) with the response data assumed to follow a Poisson distribution. One crucial assumption that must be met in Poisson regression is that the variance of the dependent variable is equal to the mean (equidispersion), i.e.

$$Var(Y) = E(Y) = \mu \tag{1}$$

However, there are also violations of assumptions, such as situations where the variance is greater than the mean, which is called an overdispersion case. Conversely, the variance value is smaller than the mean, called an underdispersion case.

The case of overdispersion in Poisson regression can be seen from the statistical value of the Pearson chi-square divided by the degrees of freedom, or it can also be called by dividing the deviation value by the degrees of freedom if the result is more than one then there is overdispersion in the Poisson regression model (Cameron, A. C & Trivedi, P. K. 1998). The Negative Binomial Regression model is used to overcome the case of overdispersion in Poisson regression.

Negative Binomial Regression has been applied to several problems in various fields, such as health, insurance, and demography. Several studies have examined NB Regression, and previous research (Islam, and Koly 2019) discussed factors related to malnutrition in Bangladesh using Generalized Poisson Regression.

2. MATERIALS AND METHOD

In this study, the data used was secondary data on the number of stunting in Nusa Tenggara Timur and Badan Pusat Statistik in East Nusa Tenggara in 2021, with the number of observations being 21 sub/districts in East Nusa Tenggara.

The United Nations Children's Fund (UNICEF) states that young children from poorer households and disadvantaged areas have the poorest diets. Previous studies have also stated that economics and education (Verma, and Prasad 2021), health status (Kurnia, et al. 2021), and access to drinking water and sanitation (Cameron,et al, 2021) significantly affect the prevalence of stunting. Considering the intervention factors in the particular index for stunting handling, several predictor variables were determined, such as infants with complete immunization, low birth weight of infants, intake of baby foods such as exclusive breastfeeding, additional vitamin A for toddlers, use of blood-added tablets, nutritional counseling, and pregnancy consultation for pregnant women, Integrated healthcare center attendance, percentage of poor people, children's preschool participation, improvement of drinking water, improved sanitation, families with beneficiary status.

The research variables used in this study divide into the predictor variable (Y) and the response variables (X)—the details of the structure of predictor variables and response variables as shown in Table 1 List of Variable Names and Descriptions.

Table 1. decriptions

Variables Names		Descriptions
Response Variables:		
Number of Stunting	(Y)	Number of children 0-59 months (under 5 years) with a height of < -2SD from toddler growth standards (based on the World Health Organization / WHO)
Predictor Variables:		
Complete immunization	(X1)	Percentage of children 0–59 months received minimal complete immunization ($BCG = 1, DPT = 3, Polio = 3, HB = 3,$ and $Measles = 1, Hepatitis\ B = 3$).
Percentage of Poor People	(X2)	Percentage of the population below the poverty line to all children under five in the same period.
Pregnant women get iron and folic acid supplementation (IFA)	(X3)	Percentage of pregnant women that take blood supplement tablets at least 90 tablets during pregnancy towards all pregnant women in the same period.
The presence of an Integrated healthcare center	(X4)	Percentage of districts implementing that are active in integrated healthcare center development.
Pregnancy consultation for pregnant women	(X5)	Percentage of pregnant women in a village receiving services antenatal 4 times towards all pregnant women in the same period.

Low birth weight	(X6)	Percentage of babies 0-59 months with low birth weight ($< 2{,}5\ kg$) to all babies in the same period.
Toddlers get exclusive breastfeeding.	(X7)	Percentage of children 0-23 months get exclusive breastfeeding for all children 0-23 in the same period.
Children's Participation in early childhood education	(X8)	Percentage of Participation of Children Aged < 6 years in Early Childhood Education
Improve water	(X9)	percentage of households with access to decent drinking water to the number of households.
Proper sanitation	(X10)	Percentage of access to sanitation (domestic wastewater) feasible for households to the number of households.
Families with beneficiary status	(X11)	Percentage of beneficiary families of the First 1,000 Days of Life who have received a variation of Non-Cash Food Assistance against total beneficiary families of First 1,000 Days of Life.

Generalized Linear Models (GLM) refer to a broader class of models popularized by McCullagh and Nelder. In this model, the response variables y_i is assumed to follow the distribution of exponential families with μ_i The mean, which is assumed to be some function that is often nonlinear from $x_i^T\beta$. Some would call it "nonlinear" because μ_i is often a nonlinear function of a covariate, but McCullagh and Nelder consider it linear because covariates affect the y_i distribution only through a linear combination of $x_i^T\beta$.

A component for each GLM, 1) Random Component, is used to determine the response variable's probability distribution. 2) Systematic Component, determine explanatory variables $(x_1, x_2, \dots, x_k)$ On models or, more specifically, their linear combinations. 3) The Link function, η atau $g(\mu)$, determines the relationship between random and systematic components. The Link function shows how the expected response value relates to a linear combination of explanatory variables.

The Poisson regression model is one of the Generalized Linear Models (GLM). Poisson regression is a regression that can describe the relationship between the response variable (y), where the response variable is Poisson-distributed with the independent variable (x). If μ_i Is the mean success that occurs in a given time interval and is assumed to be, μ_i do not change from one data point to another independently, then μ_i can be modeled as a function of k predictor variables (Myers, R.H. 1990). And the link function used logs, namely $\ln(\mu_i) = \eta_i$, so the logarithm of the equation,

$$\ln E(y_i|x_i) = \ln(\mu_i) = \eta_i = \beta_o + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} \quad (2)$$
$$\mu_i = \exp(x_i^T \beta) = exp(\beta_o + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik}) \quad (3)$$

The Poisson regression method has conditions where the mean value is equal to the variance of the response variable (Khoshgoftaar, et al. 2004). However, there are certain circumstances where the mean value is not equal to the variance of the response variable, known as over/under dispersion. Estimated dispersion can be measured using deviance or Pearson's Chi-Square divided by free degrees. The data is an overdispersion of the estimated dispersion of the dispersion greater than one and vice versa. There are regression models that can overcome this over/under dispersion problem, namely Negative Binomial Regression. The Negative Binomial Regression model is similar to the Poisson regression model in that it is a GLM model.

To test the parameters, one of the methods is MLE. The MLE is a parameter estimation method used when the distribution is known. A partial derivative of the $ln-$likelihood function can estimate parameters through the MLE method. The $ln-$likelihood function for Poisson regression is:

$$\ln L(\beta) = \sum_{i=1}^{n} [y_i(x_i^T \beta) = \exp(x_i^T \beta) = \ln(y_i)] \quad (4)$$

Two likelihood functions related to the regression model obtained are first determined to test the feasibility of the Poisson regression model. The two functions are $L(\widehat{\Omega})$ and $L(\widehat{\omega})$, which are complete model likelihood values involving and without involving predictor variables.

This study uses the Maximum Likelihood Ratio Test (MLRT) method to determine the statistical test and test the parameters of the Poisson regression model with the hypothesis:

H_0: $\beta_1 = \beta_2 = \cdots = \beta_k = 0$

H_1: there is at least one $\beta_j \neq 0, j = 1,2, \ldots k$

Test statistics for the feasibility of Poisson regression models:

$$G = -2[ln\left(\frac{L(\widehat{\omega})}{L(\widehat{\Omega})}\right) = 2\left(L\left(\widehat{\Omega}\right) - L(\widehat{\omega})\right) \quad (5)$$

The decision is to reject H_0 if $G_{test} \geq \chi^2_{v,\alpha}$ with the number of model parameters under the population reduced by the number of parameters below, H_0 Poisson regression model parameters that have been generated from parameter estimation do not necessarily have a significant influence on the model. For this reason, it is necessary to test the parameters of the Poisson regression model individually. Using the following hypothesis:

H_0: $\beta_i = 0$ (the effect of the variable is not significant)

H_1: $\beta_i \neq 0$ (The effect of the variable is significant)

With test statistics:

$$t_i = \frac{\widehat{\beta_i}}{SE(\widehat{\beta_i})} \quad (6)$$

Reject H_0 if $\left|t_{hitung}\right| > t_{\frac{\alpha}{2},v}$, where α is the significance level, and v is the free degree.

Furthermore, to determine the best model for number of stunting, one of them uses the *Akaike Information Criterion* (AIC) (Bozdogan,2000), which is defined as:

$$AIC = -2lnL(\hat{\theta}) + 2k \quad (7)$$

where $L(\hat{\theta})$ Is the likelihood value, and k is the number of parameters. The best regression model is the one with the smallest AIC value.

There is a unique event where the mean value will be equal to the variance when using Poisson regression. What if there is a violation of the Poisson distribution assumption, where the variance value of the response is greater than the mean? Then there will be a condition called overdispersion. In addition to the reasons for violating the Poisson distribution assumption, correlations between consumption, excess zeros, and outliers in the data can also result in overdispersion. One way to detect overdispersion is to look at the deviance value, namely:

$$D = 2\sum_{i=0}^{n} \log\left(\frac{y_i}{\mu_i}\right) \quad (8)$$

If the quotient between the D statistical value to the free degree or the statistical X^2 to the free degree is more than 1, the indication that there has been an overdispersion in the Poisson regression model.

3. RESULTS AND DISCUSSION

This study modeled stunting in East Nusa Tenggara Province in 2021 using the Negative Binomial Regression model. The factors used, including the percentage of infants who get complete immunization (X_1), the percentage of the population below the poverty line (X_2), the percentage of pregnant women taking blood supplement tablets (X_3), the percentage of household attendance at the implementation of Integrated healthcare center development (X_4), the percentage of pregnant women received antenatal services 4 times (X_5), the percentage of low birth weight babies (X_6), the percentage of toddlers get exclusively breastfeed (X_7), percentage of child participation in early childhood education (X_8), percentage of households with drinking water that feasible (X_9), percentage of households with good sanitation (X_{10}), percentage of families with beneficiary status (X_{11}). Before modeling these factors, it is necessary to conduct descriptive statistical analysis to determine each variable's characteristics. A descriptive statistical analysis of the number of stunting in East Nusa Tenggara Province in 2021 and the variables that influence it are presented in the following table:

Table 2. Descriptive Statistics

	Min.	Max	Mean	Std. Deviation
Y	399	16904	3831.429	3498.331
X_1	50.86	82.25	67.3019	8.53815
X_2	11.14	34.27	22.3471	6.74715
X_3	48.60	100.00	84.1333	13.31087
X_4	59.80	97.20	84.7714	8.67566
X_5	43.40	90.50	67.1905	12.63772
X_6	8.15	29.31	15.8986	6.09799
X_7	91.95	100.00	97.1029	1.99962
X_8	12.51	34.76	25.9376	5.33277
X_9	9.10	95.50	67.5905	19.48794
X_{10}	20.20	98.10	69.0286	20.44126
X_{11}	0.80	100.00	57.6524	38.82076

It is known that the average number of stunting in East Nusa Tenggara is 26.41927%. When the prevalence is calculated, it is still more than 20%, this shows that stunting in East Nusa Tenggara is still classified as acute.

Based on table 2, it can be seen that the variables X_3 and X_4 have an average value of more than 80%. This means that in almost all districts in East Nusa Tenggara, pregnant women consume blood supplement tablets, active Integrated healthcare center development, and X_7, the variable of 0-23 months of children getting exclusive breastfeeding reaches 97%.

Poisson Distribution conformity test was performed on the dependent variable using Kolmogorov Smirnov Test, with hypothesis, H_0: Data on stunting sufferers in East Nusa Tenggara 2021 distributed by Poisson; H_1: Data on Stunting Patients in East Nusa Tenggara in 2021 is not distributed by Poisson. Testing the Poisson distribution is carrying out by a test using the Kolmogorov Smirnov Test. Based on the Kolmogorov Smirnov test results, a p-value < $2.2e{-16}$ was obtained, where the significance value was less than 0.05. So the decision of the hypothesis is to reject H_0, it means the number of under-five stunting children is not Poisson distributed. But an overdispersion test will still be carried out using Poisson regression.

The next step is the multicollinearity test, which aims to determine whether or not there is a deviation from the classical assumption of multicollinearity, namely the existence of a linear relationship between independent variables in the regression model. Testing the presence or absence of symptoms of multicollinearity is carried out by looking at the value of VIF (Variance Inflation Factor) and Tolerance. The formula used to get the VIF value according to the equation:

$$VIF = \frac{1}{Tolerance} \tag{8}$$

Table 3. shows the results of the multicollinearity test on one variable with another variable

Table 3. The results of the multicollinearity test

Parameter	Collinearity Statistic	
	Tolerance	VIF
$X1$	0.346	2.888
$X2$	0.151	6.632
$X3$	0.389	2.572
$X4$	0.289	3.459
$X5$	0.200	5.009
$X6$	0.331	3.025
$X7$	0.443	2.256
$X8$	0.282	3.543
$X9$	0.289	3.466
$X10$	0.478	2.092
$X11$	0.467	2.141

One of the conditions that must be met in the regression analysis is that there is no case of multicollinearity between predictor variables. Therefore, a multicollinearity test was performed on the observed data. Multicollinearity problems can be detected by looking at the Tolerance value or the Variance Inflation Factor (VIF) value of the observed data. With hypothesis, H_0 : The regression model has a multicollinearity problem; H_1 : The regression model does not have a multicollinearity problem. The test criterion used is to reject H_0 if all predictor variables have VIF < 10 and Tolerance > 0.1. From table 3, it can be seen that the regression model does not have a multicollinearity problem.

The regression model is said not to contain multicollinearity if the VIF value is below 10 and the Tolerance value is more than 0.1. Based on the multicollinearity test in Figure 1, the VIF value in each variable is less than 10 and has a Tolerance value of more than 0.1. So it can be concluded that there is no high enough correlation in the predictor variable.

After testing cases of multicollinearity between variables, it was found that the test results showed no cases of multicollinearity. So it can be continued on modeling through Poisson regression. After knowing the estimated value of the Poisson regression model parameters, then testing was carried out simultaneously and partially. Concurrent testing of the significance of Poisson regression model parameters aims to determine the simultaneous effect of independent variables on dependent variables

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Table 4. Parameter significance test result (β) of Poisson regression model

	Parameter	Coefficient	Z Value	P-value	Signifcance
	β_0	8,172035	2146,648	< 2e-16	Significant
	β_1	0,162401	25,499	< 2e-16	Significant
	β_2	0,362887	34,735	< 2e-16	Significant
	β_3	0,141131	22,073	< 2e-16	Significant
	β_4	0,013099	1,871	0.0613 .	Insignificant
	β_5	0,245582	27,151	< 2e-16	Significant
	β_6	0,168967	23,009	< 2e-16	Significant
	β_7	-0,042754	-7,352	1.95e-13	Significant
	β_8	-0,391033	-49,07	< 2e-16	Significant
	β_9	-0,330355	-47,599	< 2e-16	Significant
	β_{10}	0,009466	1,749	0.0803 .	Insignificant
	β_{11}	0,06017	10,851	< 2e-16	Significant
	Deviance: 35996		Degree of Freedom: 9		
	AIC: 36225				

$\alpha = 0,05$

Based on Table.4, there are 9 predictor variables that significantly explain the response variable for the number of stunting in East Nusa Tenggara in 2021, namely complete immunization (X_1), the percentage of the population below the poverty line(X_2), the percentage of pregnant women taking blood supplement tablets (X_3), the percentage of pregnant women received antenatal services 4 times (X_5), the percentage of low birth weight babies(X_6), the percentage of toddlers get exclusively breastfeed (X_7), percentage of child participation in early childhood education (X_8), percentage of households with drinking water that feasible (X_9), percentage of families with beneficiary status (X_{11}). for having p-value $< \alpha = 0{,}05$.So based on Table.2 a Poisson regression model ie:

$$\hat{\mu} = \exp(8{,}172035 + 0{,}162401\mathrm{X}_1 + 0{,}162401\mathrm{X}_2 + 0{,}141131X_3 + 0{,}245582\mathrm{X}_5 + 0{,}168967\mathrm{X}_6 - 0{,}042754\,\mathrm{X}_7 - 0{,}391033X_8 - 0{,}330355\mathrm{X}_9 + 0{,}06017\mathrm{X}_{11} \quad (8)$$

Furthermore, it detects cases of overdispersion with the quotient of the residual deviation and the degree of freedom, namely $35996 : 9 = 3999{,}5 > 1$, so the GLM model for Poisson's distributed response data experienced a case of overdispersion, which resulted in the Poisson regression model being incompatible. The regression model that is expected to overcome overdispersion is the Binomial Negative regression model.

Negative Binomial Regression, recognized as a Gamma-Poisson mixture model, is employed for analyzing numerical data in situations where overdispersion is observed within the Generalized Linear Model (GLM) framework for data with a Poisson-distributed response variable (Melliana,et al. 2013). The regression parameters (β) are estimated using the Maximum Likelihood Estimation (MLE) method. Significance testing of both simultaneous and partial parameters in the Negative Binomial regression model is performed based on the results of the Fisher scoring iteration, which converges in the initial iteration.

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Table 5. Parameter significance test result ($\boldsymbol{\beta}$) of Negative Binomial regression model

Parameter	Coefficient	Z Value	P-value	Signifcance
β_0	10,4071	56.790	< 2e-16	Significant
β_1	-0,022	-0,694	0,04	Significant
β_2	0,0186	0,456	0,098	Insignificant
β_3	-0,0928	-2,448	-0,019	Significant
β_4	-0,0206	-0,907	0,054	Insignificant
β_5	0,0374	1,695	0,081	Insignificant
β_6	0,1937	3,666	0,027	Significant
β_7	-0,0072	-0,06	0,228	Insignificant
β_8	-0,0535	-1,358	0,240	Insignificant
β_9	0,0431	1,592	0,096	Insignificant
β_{10}	0,0174	1,371	0,062	Insignificant
β_{11}	0,0116	2,047	0,023	Significant

Deviance: 22,485
AIC: 403,82

$\alpha = 0{,}05$

Next, we conduct simultaneous testing. According to Table 5, a deviance value of 22,485, which is greater than $\chi^2_{10;0.05}$ or 18.30704, indicates the presence of variables that significantly contribute to the Negative Binomial regression model. Following this, a partial test is performed. As per the R output results in Table 5, the parameters $\beta_0, \beta_1, \beta_3, \beta_6$ and β_{11} show a $|Z_{observed}|$ value greater than $Z_{(0{,}05/2)} = 1{,}96$, seggesting that the variables X_1, X_3, X_6 and X_{11} significantly explain the response variables. From Table 5, among 11 predictor variables, 4 are found to significantly influence the response variable Y as they have a p-value less than $\alpha = 0{,}05$. Taking into account the significance of certain variables as shown in Table 3, the Negative Binomial regression model is re-run, this time excluding predictor variables that are not significant. The resulting Negative Binomial regression now includes only the predictor variables X_1, X_3, X_6 and X_{11}, leading to the following outcomes:

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Table 6. Result of parameter estimation ($\boldsymbol{\beta}$) of Negative Binomial regression model

Parameter	Coefficient	Z Value	P-value	Significance
β_0	10,4071	5,263	1.42e-07	Significant
β_1	-0,028790	-1,827	0,033	Significant
β_3	-0,004209	-2,334	-0,019	Significant
β_6	-0,023509	-2,764	0,017	Significant
β_{11}	0,001545	-2,350	0,014	Significant
Deviance: 22.889				
AIC: 395.91				

$\alpha = 0{,}05$

From the data presented in Table 6, it is evident that 4 predictor variables significantly impact the response variable, which in this case is the number of stunting cases in East Nusa Tenggara. These influential variables are namely complete immunization (X_1), the percentage of pregnant women taking blood supplement tablets (X_3), the percentage of low birth weight babies(X_6), and percentage of families with beneficiary status (X_{11}), each demonstrating a p-value less than $\alpha = 0.05$. Therefore, the estimated equation for the Negative Binomial regression model can be written as follows:

$$\widehat{\mu} = \exp\,(10{,}4071 - 0{,}028790X_1 - 0{,}004209X_3 - 0{,}023509X_6 + 0{,}001545X_{11} \qquad (8)$$

Based on the formulated model, the interpretation of the model can be explained as follows: 1) An increase of one unit in the persentage of complete immunization will result in a reduction of stunting cases in East Nusa Tenggara by approximately 2,87% while keeping other variables constant; 2) An increase of one unit in the percentage of pregnant women taking blood supplement tablets will result in a reduction of stunting cases in East Nusa Tenggara by approximately 0.4209% while keeping other variables constant; 3) An increase of one unit in the percentage of low birth weight babies will lead to a reduction in the number of stunting cases in East Nusa Tenggara by approximately 2,35% while keeping other variables constant; 4) Conversely, an increase of one unit in the percentage of families with beneficiary status will cause an increase in stunting cases in East Nusa Tenggara by approximately 0,1545% while keeping other variables constant.

4. CONCLUSION

In this research, Negative Binomial regression was employed as a suitable alternative to address the issue of overdispersion present in the Poisson regression model. Parameter estimation for the model was conducted using the Maximum Likelihood Estimation (MLE) method. The most optimal Negative Binomial regression model, with four predictor variables that significantly account for stunting cases in East Nusa Tenggara, includes the following variables: complete immunization, the percentage of pregnant women taking blood supplement tablets , the percentage of low birth weight babies, and percentage of families with beneficiary status. An increase of one unit in the persentage of complete immunization will result in a reduction of stunting cases in East Nusa Tenggara by approximately 2,87% while keeping other variables constant; An increase of one unit in the percentage of pregnant women taking blood supplement tablets will result in a reduction of stunting cases in East Nusa Tenggara by approximately 0.4209% while keeping other variables constant; An increase of one unit in the percentage of low birth weight babies will lead to a reduction in the number of stunting cases in East Nusa Tenggara by approximately 2,35% while keeping other variables constant; Conversely, an increase of one unit in the percentage of families with beneficiary status will cause an increase in stunting cases in East Nusa Tenggara by approximately 0,1545% while keeping other variables constant.

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