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Classification of Hypertension in Pregnant Women Using Multinomial Logistic Regression

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ABSTRACT

Maternal Mortality Rate (MMR) is still a crucial problem in Indonesia and other developing countries; one of the causes is Hypertension in Pregnancy (HDK). This study aims to classify hypertension in pregnant women based on the factors that influence it, with a case study of patients from the Obstetrics and Gynecology Specialist Clinic at the Regional General Hospital (RSUD) Dr. R. Sosodoro Djatikoesoemo Bojonegoro. The variables used were age, gravidity, gestational age, obesity, history of abortion, hypertension, and diabetes mellitus. The research method used in this study is multinomial logistic regression because it uses four categories of dependent variables, namely pregnant women without hypertension, pregnant women with chronic hypertension, pregnant women with gestational hypertension, and pregnant women with preeclampsia. The results obtained in this study were from 3 categories of hypertension in pregnant women; the influencing factors were obesity, gestational age > 36 weeks, having a history of hypertension, and diabetes mellitus, with the resulting model classification accuracy value of 79.6%, which means the classification is classified as good. This research contributes to applying statistical methods in the health sector and as a mitigation effort to help minimize the number (prevalence) of maternal deaths, especially those caused by hypertension.

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A. INTRODUCTION

Maternal mortality is defined as an indicator to monitor the health status of women (Drechsel et al., 2022). Maternal mortality is one of the 17 indicators of the *Sustainable Development Goals* (SDGs) or sustainable development goals. It is the 3rd indicator with the target of reducing the global maternal mortality rate to less than 70 per 100,000 live births by 2030. These SDGs aim to ensure a healthy life. Healthy and create well-being for people of all ages (Kassebaum et al., 2017). The Maternal Mortality Rate (MMR) in Indonesia, based on data from the Ministry of Health of the Republic of Indonesia in 2020, is 98.6 per 100,000 live births. For the province of East Java, it is 98.39 per 100,000 live births (Kementerian Kesehatan RI, 2021).

Bojonegoro is one of the districts in East Java that occupies the 9th position with the highest MMR in 2020, which is 161.80 per 100,000 live births, where for the cause of hypertension in pregnancy, as many as six pregnant women (Dinas Kesehatan Provinsi Jawa Timur, 2021). Hypertension in Pregnancy (HDK) is a condition in which pregnant women experience medical complications, with systolic blood pressure reaching 140 mmHg and diastolic blood pressure going 90 mmHg and experiencing an increase in systolic blood pressure of at least 30 mmHg and diastolic blood of at least 15 mmHg measured at least every 6 hours at different times (M. Reddy et al., 2020). Pregnant women with hypertension are at higher risk of severe complications that can threaten pregnancy, such as placental abruption, organ system failure, cerebrovascular disease, and intravascular coagulation (Riise et al., 2019). Hypertension is one of the primary triggers of maternal morbidity and infant mortality worldwide (Cameron et al., 2020). Symptoms of hypertension commonly seen during pregnancy are headache, nausea, and vomiting due to increased intracranial pressure in the scalp, blurred vision due to increased blood pressure damaging the retina of the eye, nocturia (many urination at night) due to swelling caused by increased pressure. Capillary, blood flow, and glomerular filtration are also edema-dependent (Anggreni et al., 2018).

There are several risk factors for hypertension, including internal factors such as age, gender, race, and genetics, and external factors such as obesity, smoking, and lifestyle factors such as consuming the wrong food and drink (S. Reddy & Jim, 2019). Hypertension can occur because these factors co-occur. In other words, if there is only one risk factor, there is a small risk of causing hypertension. Therefore, hypertension can be prevented by controlling its risk factors (Simamora et al., 2019). Based on this, it is necessary to anticipate efforts, including classifying hypertension in pregnant women, to analyze the factors that influence it. Thus, the implementation of reducing the incidence of hypertension in pregnant women can be more focused on the risk factors.

Research on hypertension in pregnancy has been conducted by Corrigan et al. (2021), who identified risk factors for hypertension in pregnancy. It was found that the risk factors for hypertension in pregnancy were maternal age, history of diabetes mellitus, and obesity. Lao et al. (2018) examined the characteristics between a history of previous abortions and the incidence of hypertension in pregnant women, showing that there is a relationship between a history of abortion and the incidence of hypertension in pregnancy where pregnant women with a history of previous abortions, mainly induced abortions, will reduce the risk of hypertension in pregnancy due to local injury to the endometrium caused by uterine bleeding. Caused by induced abortion will induce an inflammatory response. Sudarman et al. (2021) identified factors that have a relationship with the incidence of preeclampsia and showed that risk factors were age, gravidity, obesity, and history of diseases such as diabetes mellitus, chronic hypertension, kidney disease, and preeclampsia. Marniarti et al. (2016) examined the relationship between maternal age, gestational age, gravidity, and the incidence of hypertension in pregnancy. They found an association between maternal age, gestational age, and gravidity to the incidence of hypertension in pregnancy.

Factors that are thought to influence the incidence of hypertension in pregnant women, such as chronic hypertension, gestational hypertension, and preeclampsia, can be classified. Classification aims to group similar data collections based on specific criteria. In statistics, the classification method that can be used is the logistic regression method. Logistic regression is a method used to find the relationship between the response variable and its predictor variables in two or more categories. It is on a nominal, interval, or categorical scale (Zabor et al., 2022). Logistic regression is divided into simple logistic regression, a method used to find the relationship between one predictor variable and one response variable; binary (dichotomous), and multiple logistic regression, a technique used to find the relationship between several different predictor variables with one variable. Multiple logistic regression has a variable response model whose scale is binary (*dichotomous*), multinomial (*polychotomous*), and ordinal with one or more predictor variables where the response variable is categorical or continuous (Kuckertz et al., 2019).

The multinomial logistic regression method is a development of binary logistic regression (Zhao et al., 2022). Several studies have been conducted on multinomial logistic regression, such as the study by Ayorinde & Bhattacharya (2017), which used multinomial logistic regression to evaluate the extent of the familial risk of prenatal hypertension and preeclampsia in women born of complicated gestational hypertension pregnancies and preeclamptic pregnancies while controlling for other risk variables. The results showed that the preeclampsia inheritance pattern exhibited a dose-response effect, with women born in preeclamptic pregnancies carrying the highest risk. Preeclampsia and maternal gestational hypertension were associated with comparable increased risks in gestational hypertension. Ziert et al. (2022) used multinomial logistic regression to assess the impact of medically assisted reproduction on maternal and newborn outcomes using COVID-19 during pregnancy. The findings indicated that, although medically assisted reproduction was not the leading risk factor, women with COVID-19 who conceived through fertility therapy had a greater prevalence of unfavorable obstetrical and newborn problems than women who developed spontaneously. Alisse Hauspurg et al. (2019) used multinomial logistic regression to assess the probability of preeclampsia or gestational hypertension based on the early pregnancy blood pressure category and trajectory. The findings showed that the risk of preeclampsia and gestational hypertension in nulliparous women is independently correlated with the blood pressure category and course during the early stages of pregnancy. A more significant number of women may be identified as being at risk for preeclampsia and gestational hypertension if blood pressure categories with lower thresholds than those typically used to classify people as hypertensive are employed. In addition, the predictability of later-onset preeclampsia and gestational hypertension in pregnancy is poor, while Gunderson et al. (2023) indicate a risk of early-onset preeclampsia. Pregnancy blood pressure patterns up to 20 weeks of gestation and clinical, social, and behavioral factors could more accurately distinguish between low-to-moderate risk pregnancies and hypertensive disorders of pregnancy risk using multinomial logistic regression models with predictive performance.

Based on the studies above, many factors can cause hypertension in pregnancy, and the multinomial logistics regression is a classification method with good performance. So, in this research, we proposed to use multinomial logistic regression to classify factors that influence the incidence of hypertension in pregnant women. This research is expected to help provide input to the RSUD, Dr. R. Sosodoro Djatikoesoemo Bojonegoro, in policy-making to minimize the number (prevalence) of maternal deaths, especially those caused by hypertension.

B. METHODS

1. Multicollinearity Test

A suitable regression model should not be found among cases of multicollinearity, or there is a perfect or near-perfect correlation of the independent variables (the correlation is one or close to 1). The Variance Inflation Factor (*VIF*) is used to test multicollinearity with the formula in the following equation (Wibowo & Ridha, 2020):

$$VIF = \frac{1}{1 - R^2} \tag{1}$$

where R^2 is the regression coefficient value. If the VIF value is < 10, it can be said that there are no cases of multicollinearity among the predictor variables, and it is said that there are cases of multicollinearity between the predictor variables when the VIF value is > 10.

2. Independence Test

Using the Pearson Chi-Square Test, the independence test is used to find the relationship between the response and predictor variables. The hypotheses tested in this test are: $H_0: P_{ij} = P_{i.}\ P_{.j}$ (no relationship was found between predictor variables and response variables);$H_1: P_{ij} \neq P_{i.}\ P_{.j}$ (a relationship was found between predictor variables and response variables) with test statistics:

$$\chi^2 = \sum_{i=1}^{r}\sum_{j=1}^{c}\frac{\left(n_{ij} - \widehat{m}_{ij}\right)^2}{\widehat{m}_{ij}} \tag{2}$$

where $\widehat{m}_{ij} = \frac{n_{i.} \times n_{.j}}{n}$, and information χ^2 is *Chi-Square* test statistic value, n_{ij} is observation value for row-i and column-j, $\widehat{m}_{ij}$ is the expected value, $n_{i.}$ is the number of observations for row-i, $n_{.j}$ is the number of observations for column-j, n is the number of observations. With degrees of freedom $df = (I-1)(J-1)$, then for decision-making, reject H_0 if $\chi^2_{\text{count}} > \chi^2_{(df,a)}$ or *p-value* $< a$.

3. Multinomial Logistic Regression

Multinomial logistic regression, also known as cumulative logit (Abbaszadeh Afshar et al., 2018). In multinomial logistic regression, where the response variable is with *j* categories, the logit function to be formed is *j–1* (Blondel et al., 2023). This study uses four nominal scale response variables, resulting in three logit function equations. The form of the multinomial logistic regression model is as follows:

$$Logit\ P(Y = J) = \beta_0 + \beta_1 x_1 + \cdots + \beta_{jp} x_p \tag{3}$$

By using the logit transformation, we get three models of the logit function:

$$g_1(x) = \ln\left[\frac{P\ (Y=1)x}{P\ (Y=0)x}\right] = (\beta_{10} + \beta_{11}x_1 + \beta_{12}x_2 + \cdots + \beta_{1p}x_p) \tag{4}$$

$$g_2(x) = \ln\left[\frac{P\ (Y=2)x}{P\ (Y=0)x}\right] = (\beta_{20} + \beta_{21}x_1 + \beta_{22}x_2 + \cdots + \beta_{2p}x_p) \tag{5}$$

$$g_3(x) = \ln\left[\frac{P\ (Y=3)x}{P\ (Y=0)x}\right] = (\beta_{30} + \beta_{31}x_1 + \beta_{32}x_2 + \cdots + \beta_{3p}x_p) \tag{6}$$

Based on the three logit functions, the probability of the multinomial logistic regression model is obtained as follows:

$$P(y=0|x) = \pi_0(x) = \frac{1}{1 + \exp g_1(x) + \exp g_2(x) + \exp g_3(x)} \tag{7}$$

$$P(y=1|x) = \pi_1(x) = \frac{\exp g_1(x)}{1 + \exp g_1(x) + \exp g_2(x) + \exp g_3(x)} \tag{8}$$

$$P(y=2|x) = \pi_2(x) = \frac{\exp g_2(x)}{1 + \exp g_1(x) + \exp g_2(x) + \exp g_3(x)} \tag{9}$$

$$P(y=3|x) = \pi_3(x) = \frac{\exp g_3(x)}{1 + \exp g_1(x) + \exp g_2(x) + \exp g_3(x)} \tag{10}$$

4. Simultan Test

Simultan test is carried out to determine the significance of the β parameter to the overall response variable using the *likelihood ratio* value or the G test. The hypotheses tested in the simulation trial are: H_0 : $\beta_1 = \beta_2 = \beta_p = 0$ (no effect was found between a set of predictor variables and response variables); H_1 : At least one $\beta_j \neq 0, j = 1,2,3,\dots,p$ (at least one predictor variable is found that affects the response variable) with test statistics:

$$G = -2ln\left[\frac{L_0}{L_k}\right] = -2[ln(L_0) - ln(L_k)] = -2(L_0 - L_k) \tag{11}$$

where L_0 is the likelihood without the predictor variable and L_k is the *likelihood* with the predictor variable. The decision-making criteria reject H_0 if the G test value > $\chi^2_{(\alpha,df)}$ or *p-value* < α.

5. Partial Test

A partial test is needed to determine the significance of the β parameter on the individual response variables using the *Wald* Test. The hypotheses tested in the partial test are: H_0 : $\beta_j = 0$ (no effect was found between the predictor variables to-j on the response variable); H_1 : $\beta_j \neq 0, j = 1,2,\dots,p$ (found the influence of predictor variables on response variables) with test statistics:

$$W = \left(\frac{\hat{\beta}_J}{SE(\hat{\beta}_J)}\right)^2 \tag{12}$$

Where $\hat{\beta}_J$ is the estimated parameter to-j and $SE(\hat{\beta}_J)$ is the estimated standard error of $\hat{\beta}_J$. For decision-making, reject H_0 if W value $> \chi^2_{(\alpha,df)}$ or *p-value* $< \alpha$.

6. The Goodness of Fit Test

The goodness of fit test is used to determine whether the resulting model is feasible using the *Hormer Lomeshow* Test by looking at the *Chi-Square* value. The hypotheses in the model suitability test are: $H_0 =$ Model fits (no significant difference was found between the observed results and the possible model predictions); $H_1 =$ The model does not fit (a significant difference was found between the observations and the possible model predictions) with test statistics:

$$\chi^2 = \sum_{j=1}^{J} \frac{(y_j - n_j\hat{\pi}_j)^2}{n_j\hat{\pi}_j\left(1-\hat{\pi}_j\right)} \tag{13}$$

where n_j is the number of observations category to-j, $\hat{\pi}_j$ is the probability of the categorical response variable to-j, and y_j is the value of the response variable category to-j. With decision-making reject H_0 jika $\chi^2_{\text{count}} > \chi^2_{(\alpha,df)}$ or *p-value* $< \alpha$.

7. Classification Accuracy

The multinomial logistic regression model resulted in the classification of the incidence of hypertension in pregnant women based on the factors that influence it. The possibility of misclassification can be measured using the *Apparent Error Rate* ($APER$) value (Farida et al., 2022). The smaller the $APER$ value, the better the classification accuracy. The $APER$ formula is as follows:

$$APER = \frac{nn_{1m} + nn_{2m} + nn_{3m} + nn_{4m}}{n_1 + n_2 + n_3 + n_4} \tag{14}$$

where $n_{1m}, n_{2m}, n_{3m}, n_{4m}$ is the number of mispredicted classification data, and n_1, n_2, n_3, n_4 is the number of data. By calculating the classification accuracy of $1 - APER$.

8. Data

This study uses secondary data from medical record data in the Obstetrics and Gynecology Specialist poly at Dr. R. Sosodoro Djatikoesoemo Bojonegoro from September 2022 to November 2022, 184 hypertension patients in pregnant women and 375 hospitalized patients. The variables that will be used in this study consist of the response variable (Y), namely the incidence of hypertension in pregnant women with four categories, namely Pregnant Women without Hypertension (Y_0), Pregnant Women with Chronic Hypertension (Y_1), Pregnant Women with Gestational Hypertension (Y_2) and Pregnant Women with Preeclampsia (Y_3) with predictor variables (X), namely Age (X_1), Gravidity (X_2), Obesity (X_3), Gestational Age (X_4), History of Abortion (X_5), History of Hypertension (X_6) and a History of Diabetes Mellitus (X_7). The following is a sample of research data shown in Table 1.

Table 1. Research Data Sample

Num.	Y	X_1	X_2	X_3	X_4	X_5	X_6	X_7
1	Chronic Hypertension	40	3	Yes	36	0	Have	Don't Have
2	Don't Have	21	1	No	11	0	Don't Have	Don't Have
3	Don't Have	19	1	No	32	0	Don't Have	Don't Have
4	Preeclampsia	32	2	No	36	1	Have	Don't Have
5	Don't Have	42	3	No	19	0	Don't Have	Don't Have
6	Don't Have	23	1	No	31	0	Don't Have	Don't Have
7	Don't Have	28	2	No	24	0	Don't Have	Don't Have
8	Chronic Hypertension	37	4	Yes	39	1	Have	Don't Have
9	Don't Have	38	4	No	37	2	Don't Have	Don't Have
10	Preeclampsia	32	2	Yes	36	1	Have	Have
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
93	Gestational Hypertension	43	3	Yes	38	0	Have	Don't Have

C. RESULT AND DISCUSSION

1. Multicollinearity Test

This study determined the presence or absence of multicollinearity cases by looking for the *Variance Inflation Factor* (VIF) value. Table 2 shows the results of the multicollinearity test.

Table 2. Multicollinearity Test Results

Code	Variable	VIF Value
X_1	Age	1.149
X_2	Gravity	1.307
X_3	Obesity	1.352
X_4	Gestational Age	1.229
X_5	Abortion History	1.506
X_6	History of Hypertension	1.541
X_7	History of Diabetes Mellitus	1.218

Based on Table 2, it is known that the VIF value in all predictor variables is <10. This proves that there are no cases of multicollinearity among the predictor variables used. So that all the predictor variables will be used in subsequent regression modeling.

2. Independence Test

The independence test is used to determine whether there is a relationship between the predictor variable and the response variable using the *Pearson Chi-Square* test value. The results of the independence test are presented in Table 3.

Table 3. Independence Test Results

Code	Variable	χ^2count	χ^2table	*p-value*	Decision
X_1	Age	3.764	7.814	0.288	Accept H_0
X_2	Gravity	1.677	7.814	0.642	Accept H_0
X_3	Obesity	32.641	7.814	0.000	Reject H_0
X_4	Gestational Age	27.411	7.814	0.000	Reject H_0
X_5	Abortion History	3.317	7.814	0.345	Accept H_0
X_6	History of Hypertension	52.074	7.814	0.000	Reject H_0
X_7	History of Diabetes Mellitus	16.158	7.814	0.001	Reject H_0

Table 3 shows that the variables obesity (X_3), gestational age (X_4), history of hypertension (X_6) and a history of diabetes mellitus (X_7) have a value of χ^2 count > χ^2 table and *p-value* < 0,05, which means it meets the criteria, so these variables can be continued as a model in the next test. The variables of age (X_1), gravidity (X_2) and history of abortion (X_5) also have a value of χ^2 count > χ^2 table, and *p-value* < 0,05 means that it does not meet the criteria, so these variables must be excluded and cannot be continued in the next test.

3. Multinomial Logistic Regression Model

After conducting a descriptive analysis to find out the initial description of the incidence of hypertension in pregnant women at Dr. R. Sosodoro Djatikoesoemo Bojonegoro, the next step is to form a multinomial logistic regression model. The method used in estimating the logistic regression parameters is the *Maximum Likelihood* method. Table 4 shows the estimated values and the results of the parameter significance test for the logistic regression model.

Table 4. Multinomial Logistics Regression Parameter Estimator

Incident	Parameter Estimator ($\hat{\beta}_{jk}$)	Coefficient
Pregnant Women with Chronic Hypertension (Y_1)	Intercept	-8.856
	Obesity (X_3)	3.468
	Gestational Age (X_4)	5.303
	History of Hypertension (X_6)	5.615
	History of Diabetes Mellitus (X_7)	3.074
Pregnant Women with Gestational Hypertension (Y_2)	Intercept	-10.144
	Obesity (X_3)	5.767
	Gestational Age (X_4)	5.303
	History of Hypertension (X_6)	4.976
	History of Diabetes Mellitus (X_7)	3.278
Pregnant Women with Preeclampsia (Y_3)	Intercept	-9.817
	Obesity (X_3)	4.299
	Gestational Age (X_4)	5.672
	History of Hypertension (X_6)	6.427
	History of Diabetes Mellitus (X_7)	0.589

Based on the parameter estimation results in Table 4, the comparison category is pregnant women without hypertension (Y_0), the logistic regression model for the incidence of hypertension in pregnant women is based on the factors that influence it at the RSUD Dr. R. Sosodoro Djatikoesoemo Bojonegoro as follows:

$$g_1(x) = -8.856 + 3.468x_{3(i)} + 5.303x_{4(i)} + 5.615x_{6(i)} + 3.074x_{7(i)}$$
$$g_2(x) = -10.144 + 5.767x_{3(i)} + 5.303x_{4(i)} + 4.976x_{6(i)} + 3.278x_{7(i)}$$
$$g_3(x) = -9.817 + 4.299x_{3(i)} + 5.672x_{4(i)} + 6.427x_{6(i)} + 0.058x_{7(i)}$$

where $g_1(x)$ is the logit function of the chronic hypertension category, $g_2(x)$ is the logit function of the gestational hypertension category and $g_3(x)$ is the logit function of the preeclampsia category.

4. Simultan Parameter Test

To find out whether there are predictor variables that affect the model. The following are the overall test results shown in Table 5.

Table 5. Simultan Parameter Test Results

	G Test	$\chi^2_{\alpha,df}$	*p-value*
Model	113.387	21.026	0.000

Based on Table 5, the G-test value of each predictor variable is 113,387, while the value of $\chi^2_{\alpha,df}$ was obtained from the *Chi-Square* table is 21,026, and the *p-value* is 0.000. These results indicate that the predictor variables significantly affect the dependent variable together.

5. Partial Parameter Test

Partial parameter tests were conducted to determine whether each predictor variable was significant or not on the multinomial logistic regression model. After partial testing, the parameter results are obtained, as shown in Table 6.

Table 6. Partial Parameter Test Results

Response Variable	Predictor Variable	Wald	*p-value*	Decision
Pregnant Women with Chronic Hypertension (Y_1)	Constant	13.138	0.000	Reject H_0
	Obesity (0)	5.956	0.015	Reject H_0
	Gestational Age >36 Weeks (0)	8.474	0.004	Reject H_0
	Have a History of Hypertension (0)	10.276	0.001	Reject H_0
	Have a History of DM (0)	4.339	0.037	Reject H_0
Pregnant Women with Gestational Hypertension (Y_2)	Constant	15.198	0.000	Reject H_0
	Obesity (0)	12.147	0.000	Reject H_0
	Gestational Age >36 Weeks (0)	9.191	0.002	Reject H_0
	Have a History of Hypertension (0)	8.146	0.004	Reject H_0
	Have a History of DM (0)	4.675	0.031	Reject H_0
Pregnant Women with Preeclampsia (Y_3)	Constant	12.856	0.000	Reject H_0
	Obesity (0)	7.446	0.006	Reject H_0
	Gestational Age >36 Weeks (0)	7.820	0.005	Reject H_0
	Have a History of Hypertension (0)	12.057	0.001	Reject H_0
	Have a History of DM (0)	0.110	0.740	Accept H_0

Based on Table 6 above, the variables that have a significant effect on the incidence of hypertension in pregnant women in each category are Age (X_1), Obesity (X_3), History of Hypertension (X_5) and a History of Diabetes Mellitus (X_7), so the final multinomial logistic regression model is obtained as follows:

$$g_1(x) = -8.856 + 3.468x_{3(0)} + 5.303x_{4(0)} + 5.615x_{6(0)} + 3.074x_{7(0)}$$
$$g_2(x) = -10.144 + 5.767x_{3(0)} + 5.303x_{4(0)} + 4.976x_{6(0)} + 3.278x_{7(0)}$$
$$g_3(x) = -9.817 + 4.299x_{3(0)} + 5.672x_{4(0)} + 6.427x_{6(0)} + 0.058x_{7(0)}$$

6. The goodness of fit test

The logistic regression model that has been formed is then tested for suitability of the model to evaluate the fit between the observations and the model using the *Pearson Chi-Square* test. Table 7 below shows the decision-making of the model goodness of fit test.

Table 7. The Goodness Of Fit Test Result

	χ^2 **count**	$\chi^2_{\alpha,df}$	***p-value***
Pearson	30.327	43.772	0.861

Based on the *Pearson Chi-Square* test table, the value is $\chi^2_{\alpha,df} = \chi^2_{0.05,30} = 43{,}772$. Based on Table 7, the test value χ^2 count < $\chi^2_{\alpha,df}$= 30,327 < 43,7729, and the *p-value* > 0,05, which is 0,861, means that the resulting model is appropriate or there is no significant difference between the observations. With possible forecasts of the model so that the model can be used.

7. Parameter Coefficient Interpretation

Interpretation can be made by looking at the odds ratio value in Table 8.

Table 8. Odds Ratio Results

Response Variable	Predictor Variable	Exp (B)
Pregnant Women with Chronic Hypertension (Y_1)	Constant	
	Obesity (0)	32.081
	Gestational Age >36 Weeks (0)	200.872
	Have a History of Hypertension (0)	274.387
	Have a History of DM (0)	21.632
Pregnant Women with Gestational Hypertension (Y_2)	Constant	
	Obesity (0)	319.696
	Gestational Age >36 Weeks (0)	200.873
	Have a History of Hypertension (0)	144.909
	Have a History of DM (0)	26.520
Pregnant Women with Preeclampsia (Y_3)	Constant	
	Obesity (0)	73.638
	Gestational Age >36 Weeks (0)	290.692
	Have a History of Hypertension (0)	618.597
	Have a History of DM (0)	1.802

Based on the results of the Odds Ratio on the value of Exp (B) in each model that has been obtained previously, it can be interpreted as:

a. Logit function of chronic hypertension category ($g_1(x)$):
   1) Compared with pregnant women who do not have hypertension, pregnant women with obesity conditions are more likely to experience chronic hypertension by 32,081 times compared to pregnant women with non-obese conditions.
   2) Compared with pregnant women who do not have hypertension, pregnant women with gestational age >36 weeks are more likely to experience chronic hypertension by 200,872 times compared to pregnant women with gestational age <36 weeks.

3) Compared with pregnant women who do not have hypertension, pregnant women with a history of hypertension are more likely to experience chronic hypertension by 274,387 times compared to pregnant women who do not have a history of hypertension.
4) Compared with pregnant women who do not have hypertension, pregnant women with a history of diabetes mellitus are more likely to experience chronic hypertension by 21,632 times compared to pregnant women who do not have a history of diabetes mellitus.

b. Logit function for gestational hypertension category ($g_2(x)$):
   1) Compared with pregnant women who do not have hypertension, pregnant women with obesity conditions are more likely to experience gestational hypertension by 319,696 times compared to pregnant women with non-obese conditions.
   2) Compared with pregnant women who do not have hypertension, pregnant women with gestational age >36 weeks are more likely to have gestational hypertension by 200,873 times compared to pregnant women with gestational age <36 weeks.
   3) Compared with pregnant women who do not have hypertension, pregnant women with a history of hypertension are more likely to have gestational hypertension by 144,909 times compared to pregnant women with no history of hypertension.
   4) Compared with pregnant women who do not have hypertension, pregnant women with a history of diabetes mellitus are 26,520 times more likely to experience gestational hypertension than pregnant women who do not have a history of diabetes mellitus.

c. Logit function of preeclampsia category ($g_3(x)$):
   1) Compared with pregnant women who do not have hypertension, pregnant women with obesity are more likely to experience preeclampsia by 73,678 times compared to pregnant women with non-obese conditions.
   2) Compared with pregnant women who do not have hypertension, pregnant women with gestational age >36 weeks are more likely to experience preeclampsia by 290,692 times compared to pregnant women with gestational age <36 weeks.
   3) Compared to pregnant women who do not have hypertension, pregnant women with a history of hypertension are 618,597 times more likely to experience preeclampsia compared to pregnant women who do not have a history of hypertension.
   4) Compared with pregnant women who do not have hypertension, pregnant women with a history of diabetes mellitus are more likely to experience preeclampsia by 1,802 times compared to pregnant women who do not have a history of diabetes mellitus.

8. Classification Accuracy

The classification accuracy was used to assess whether the model is correct by looking at its classification predictions based on the model that has been formed. Here is the result, seperti terlihat pada Table 9.

Table 9. Classification Accuracy Results

Observation	Y_0	Y_1	Y_2	Y_3
Y_0	54	0	1	1
Y_1	1	3	5	3
Y_2	2	0	10	3
Y_2	0	0	3	7

$$APER = \frac{0+1+1+1+5+3+2+0+3+0+0+31}{121} = 0.2043\ x\ 100\% = 20.4\%$$

Classification Accuracy is: $1 - 20.4\% = 79.6\%$; which is categorized as good. Classification accuracy in the resultant logistic regression model is computed using the overall APER value of 79.6%. Based on the factors influencing the incidence of hypertension in pregnant women at RSUD, Dr. R. Sosodoro Djatikoesoemo Bojonegoro, multinomial logistic regression is deemed appropriate for use in classifying the data, with a classification accuracy value of over 50%.

In general, it can be seen that pregnant women who experience hypertension are mostly experienced by mothers with excess body weight (obesity). This study supports the research of Corrigan et al. (2021) that pregnant women with obesity are at risk of hypertension. This is because women with obesity conditions have lower concentrations of antioxidants in the blood, and these antioxidants have a role in inhibiting the occurrence of hypertension in pregnant women, especially preeclampsia. As for pregnant women with gestational age > 36 weeks at risk of hypertension, this study is supported by research by Marniarti et al. (2016) when entering the third trimester, especially gestational age > 36 weeks, they are prone to hypertension, because the older gestational age will support the ischemia theory of the placental implantation area to identify various clinical symptoms of preeclampsia. Plasma levels of another potent corticoid mineral, deoxycorticosterone (DOC), in plasma will increase sharply in the third trimester.

Pregnant women with a history of hypertension and diabetes mellitus are at high risk of developing hypertension. This study follows the research of Sudarman et al. (2021) because when there is a previous history of hypertension, it will cause the blood vessels to become narrow, and this will last a long time, along with constriction of the blood vessels will make blood pressure increase and if the pregnant woman has a history of diabetes mellitus where the condition of excess glucose during pregnancy will hamper function cytotrophoblast cells (CTB) which will cause CTB migration and invasion complications, oxidative stress that causes placental hypoxia and can result in an antioxidant imbalance, which will lead to an abnormal placenta so that blood pressure increases and can develop preeclampsia.

D. CONCLUSION AND SUGGESTIONS

Based on the analysis and discussion for the classification of hypertension in pregnant women based on the factors that influence it in RSUD Dr. R. Sosodoro Djatikoesoemo Bojonegoro using multinomial logistic regression for the category of pregnant women with chronic hypertension and pregnant women with gestational hypertension influenced by obesity factors (X_3), gestational age (X_4), history of hypertension (X_6) and a history of diabetes mellitus (X_7) while the category of pregnant women with preeclampsia is influenced by obesity

(X_3), gestational age (X_4) and a history of hypertension (X_6) with a classification accuracy value of 79.6%, so it can be said that the classification of the incidence of hypertension in mothers' pregnancies based on the factors that influence it is good.

Recommendations for RSUD Dr. R. Sosodoro Djatikoesoemo is to provide prenatal counseling on the risks and hazards associated with hypertension to reduce the prevalence of the condition in pregnant women. So that the wider community, particularly pregnant women, more conscious of the significance of monitoring a pregnancy closely and controlling one's diet to protect a pregnant woman from illness. More variables believed to have an impact as risk factors for hypertension in pregnant women are anticipated to be included in the subsequent research proposals. More research data samples will also be added for more precise research results.

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