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Prediction of Extreme Poverty Levels Using the Performance of the Multiple Linear Regression Method

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Abstract

Extreme poverty is a type of poverty that is defined as a condition that cannot meet basic human needs. The Government of Indonesia through Presidential Instruction No. 4 of 2022 sets a target for the elimination of extreme poverty, but this effort requires an accurate and comprehensive data-driven approach. This study aims to build a model for predicting extreme poverty levels. The method used in this study is Multiple Linear Regression (MLR), which is able to measure the contribution of each predictor variable to the phenomenon of extreme poverty. The dataset processed in this study was sourced from the Dumai City Social and Community Empowerment Office. The dataset consisted of 2,007 extreme poverty data with predictor variables in the form of residence ownership (X1), employment (X2), income (X3), education (X4), and health insurance (X5). The results of this study show that the Multiple Linear Regression method is able to provide accurate predictions of the extreme poverty level in Dumai City with an accuracy rate of 87%. The model evaluation was carried out using three metrics based on the results of the test obtained $R = 0.674$ and $R^2 = 0.454$, which means that 45.4% of the variation in poverty status can be explained by the variables of home ownership, type of occupation, amount of income, education level, and health insurance. The ANOVA test showed a value of $F = 332.777$ with a significance of < 0.001, so the model was simultaneously significant. The regression coefficient showed that all variables had a negative and significant influence ($p < 0.05$) on poverty status, with the greatest influence coming from the type of job ($\beta = -0.304$) and amount of income ($\beta = -0.291$), followed by home ownership, health insurance, and education level. Thus, the Multiple Linear Regression method has proven to be effective in building an extreme poverty prediction system. This model can be a basic reference in supporting more targeted, measurable, and data-based socio-economic policy decision-making, especially in efforts to combat extreme poverty in a sustainable and systematic manner.

Keywords: extreme poverty, prediction, MLR, socioeconomic policy, predictive model evaluation.

1. Introduction

Extreme poverty is one of the most serious types of poverty, characterized by an individual's inability to meet basic needs [1]. Many factors that affect the condition of individual poverty in an area [2]. Poverty is also defined as a condition of deprivation or lack of welfare[3]. The United Nations defines extreme poverty as a living situation that falls below the minimum spending limit, which is equivalent to US$1.90 PPP per day [4][5]. Poverty is one of the major problems in developing countries that can hinder economic progress and human development [6]. This problem has become a global issue whose impact is very large on an individual and national scale [7]. The Indonesian government's seriousness in dealing with this problem through Presidential Instruction Number 4 of 2022 concerning the Acceleration of the Elimination of Extreme Poverty [8]. Poverty alleviation programs, as well as providing solutions that are more in line with local needs [9].

The development of artificial intelligence (AI) opens up tremendous opportunities in various sectors [10]. Including in efforts to overcome poverty globally [11]. One of them is through the use of Satellite imagery and machine learning to accurately map areas of high poverty and real time [12][13]. The use of Large Language Models (LLMs) is capable of Sorting the poverty level at the village level Opening up new avenues in cheap and measurable mass poverty monitoring [14][15]. In addition, AI also plays a significant role in Financial Inclusion Creating fairer access to financial services for previously underserved groups [16]. Information technology enables organizations and individuals to improve operational efficiency, expand the reach of communication, and generate new innovations [17].

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Previous research that discussed the Prediction of Poverty Rate in West Java Province Using the Linear Regression Algorithm, evaluated the model with three main metrics: RMSE, MAE, and MARE, which gave scores of 65,837, 53,156, and 66.47%, respectively. The results reveal that although it only involves one independent variable (years), this model can still produce predictions that are accurate enough to analyze poverty trends at the regional level [18].

Another study also discusses the Analysis and Prediction of the Percentage of Poverty in Indonesia Using the Multiple Linear Regression Method. This prediction model produces a very small MAPE value, which is 0.0008%, indicating a very high level of accuracy. The results of the analysis also show that the unemployment rate has a significant and positive effect on the poverty rate [19].

Another study also discusses the Multiple Linear Regression Model to Estimate the Unemployment Rate in West Java Province. The model was evaluated by utilizing RMSE values and determination coefficients (R^2). Optimal results were achieved through a model using preprocessing and PCA, resulting in an RMSE of 0.0148 and an R^2 of 0.5716, indicating a low rate of prediction error and good model quality in describing TPT variation in the area [20].

Another study also analyzed and predicted the value of the Human Development Index (HDI) in West Sumatra Province by referring to social and economic factors. This study applies the Multiple Linear Regression with the forward selection. The final model yields an R-squared value of 0.897 and an RMSE of 1.50, indicating that the model can explain about 89.7% of the variation in HDI and has a minimal prediction error rate [21].

Other research also discusses the problem of unemployment which remains a major challenge in West Java. The methods used are Simple Linear Regression. Model evaluation shows that the Root Mean Squared Error (RMSE) value is in the range of 15859.070 to 16086.502, depending on the attribute selection method applied. The value is quite consistent, showing that the model *Linear Regression* can provide relatively accurate predictions [22].

This study proposes a predictive approach to the extreme poverty level in Dumai City using the Multiple Linear Regression (MLR) method. MLR analysis was conducted based on socioeconomic variables using five predictor variables such as residence ownership, employment, income, education, and health insurance. This study aims to create a prediction model that uses the Multiple Linear Regression method to measure and analyze the relationship between socioeconomic variables and extreme poverty levels. The contribution of this research can help policymakers understand the factors that have a significant impact on the level of extreme poverty.

2. Methods

The research design includes several steps that will be carried out sequentially, from the data collection stage to model evaluation. Here are the stages that the framework described by the framework in Figure 1.

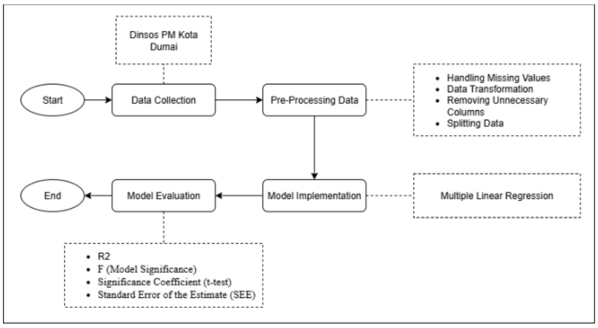

Figure 1. Framework

2.1 Data Collection

The data processed in this study is sourced from the Dumai City Social and Community Empowerment Office. The data consisted of 2,007 extreme poverty data with predictor variables in the form of housing ownership (X1), employment (X2), income (X3), education (X4), and health insurance (X5).

2.2 Pre-Processing Data

Data pre-processing is the initial process required to ensure the data is in a ready-to-use condition for analysis and model building. The steps of this study include:

(1) Handling of blank values in the pre-processing process of data, handling of blank values is carried out through imputation techniques using average or median values, depending on the distribution of data, while incomplete entries in small quantities are removed to maintain data quality. (2) Data transformation is applied to transform raw variables into more meaningful and consistent forms, including scaling adjustments and distribution of variables to suit the needs of analysis and statistical models to be used. (3) Removing unnecessary columns Columns that are irrelevant or do not contribute to the analysis and modeling process are removed to simplify the data structure and improve processing efficiency. (4) Split data after the data is cleaned and transformed, the data splitting process is carried out by separating the dataset into two parts, namely the training data and the test data, to ensure that the model can be optimally trained and

evaluated objectively against data that has never been seen before.

2.3 Application of the MLR Model

Multiple Linear Regression is a method used to analyze the relationship between one dependent variable Y and two or more independent variables X. This method is a development of Simple Linear Regression, where more than one free variable is used to predict the target variable. The stages are as follows:

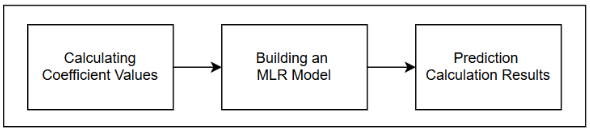

Figure 2. Multiple Linear Regression Algorithm

2.3.1 Calculating Coefficient Values

The calculation of the regression coefficient is the main step in building *a* Multiple Linear Regression (MLR) *model*. The regression coefficient shows the magnitude and direction of the influence of each independent variable on the dependent variable.

2.3.2 Multiple Linear Regression (MLR) Model

Calculations in the Multiple Linear Regression (MLR*)* model were performed to determine the linear relationship between one dependent variable (Y), namely the extreme poverty level, and several independent variables (X_1, X_2, ..., Xn) such as employment, income, education level, home ownership, and health insurance. The MLR model is generally expressed in the form of equations:

$$y_i = \beta_0 + \beta_1 x_{i,1} + \cdots + \beta_p x_{i,p} + \varepsilon_i, \quad (1)$$

ρ is an integer greater than 1. shows the observation of the - of the variable attribute ke-.$x_{i,j} ij$

2.3.3 Prediction Calculation Results

The result of this study is the achievement of a clear understanding of how much impact each variable has on the level of extreme poverty, so that the relative contribution of each variable such as home ownership, type of employment, amount of income, education level, and health insurance can be known in influencing the state of extreme poverty. In addition, the developed model is expected to be able to estimate whether a household falls into the extreme poor category or not, based on a combination of the value of these variables. The study is expected to be able to find the most statistically significant variables, so that key elements that contribute significantly to the reduction of extreme poverty can be prioritized in the formulation of appropriate policies and actions

2.4 Model Evaluation

Model evaluation was carried out to find out how accurate the regression model is in predicting extreme poverty levels. This evaluation is important to ensure that the risk score (Y) generated by the model is close to the actual value or expected value. In this study, three types of prediction error evaluations were carried out, namely:

The coefficient of determination is used to measure how much proportion of variation in dependent variables can be explained by independent variables.

$$R^2 = \frac{SS_{reg}}{SS_{total}} \quad (2)$$

SS_{reg} = Sum of Squares Regression (variation described by the model)
SS_{total} = Total Sum of Squares (total data variation)

The F (Model Significance) test measures whether all independent variables simultaneously have a significant effect on the dependent variables.

$$F = \frac{MS_{reg}}{MS_{res}} \quad (3)$$

$MS_{reg} = \frac{MS_{reg}}{df_{reg}}$
$MS_{res} = \frac{MS_{res}}{df_{res}}$

Significance Coefficient (t-test) Measures the influence of each independent variable on the variable

$$t_i = \frac{B_i}{SE_{Bi}} \quad (4)$$

B_i = Regression coefficient of the ith variable
SE_{Bi} = *Standard Error* of the coefficient of the i variable Dependent.

Standard Error of the Estimate (SEE) measures the average of the model's prediction error against the actual value.

$$SEE = \sqrt{\frac{SS_{res}}{n-k-1}} \quad (5)$$

n = Number of samples
k = Number of independent variables

3. Results and Discussions

3.1. Pre-Processing Data

The calculation of the regression coefficient is the main step in building a Multiple Regression (MLR) model. The regression coefficient shows the magnitude and direction of the influence of each independent variable on the dependent variable. The research variables are presented in the Table 1.

Table 1. Data Transformation

ID	Kepemilikan Rumah	Pekerjaan	Penghasilan	Pendidikan	Jaminan Kesehatan	Status Kemiskinan
1	2	2	1	2	3	1
2	2	2	2	2	3	1
3	4	2	2	3	3	1
4	1	2	1	3	3	1
5	1	2	1	2	3	1
6	1	2	1	2	3	1
7	4	2	3	2	3	1
8	5	3	2	3	3	1
9	6	1	1	2	3	1
10	1	1	1	1	3	1
...	...	...	...	...	...	...
2007	4	2	2	1	3	1

The data that has been collected is then transformed into numerical form based on the code on each indicator variable. This transformation process is carried out to facilitate statistical analysis and data processing using the Multiple Linear Regression prediction model.

3.4 MLR Prediction Process

The calculation of the Multiple Linear Regression (MLR) model was carried out to determine the linear relationship between one dependent variable (Y), namely the extreme poverty rate, and several independent variables (X_1, X_2, ..., Xn) such as employment, income, education level, home ownership, and health insurance. The MLR model is generally expressed in the form of equations:

3.5 Calculation Results

The results of the regression model used can explain most of the data variations and show good accuracy, making it feasible to use it as a reliable analytical tool to understand the relationship between research variables. This model not only offers a quantitative picture of the impact of each factor, but also helps to forecast future circumstances with a fairly low error rate.

After the process is carried out using the MLR model with five variables as predictors, you can see the summary model as shown in the Table 2.

Table 2. Model Summary

Type	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.674a	.454	.453	.240	.454	332.777	5	2001	.000

The results of the analysis from the Model Summary table show that the regression model made has a correlation value (R) of 0.674, which indicates a fairly strong relationship between independent variables and dependent variables. A determination coefficient (R^2) of 0.454 showed that 45.4% of the variation in extreme poverty rates could be explained by variables of health insurance, income, home ownership, education, and type of employment, while the other 54.6% were influenced by other factors outside the model. An Adjusted R^2 value that is close to the same (0.453) indicates the stability of the model with no signs of overfitting. The F test obtained a value of 332.777 with a significance level of < 0.001, indicating that simultaneously all independent variables had a significant influence on the level of extreme poverty

The overall regression model test whether it has a significant influence can be seen from the *Analysis of Variance* (ANOVA) in the Table 3.

Table 3. ANOVA

Type		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	95.932	5	19.186	332.777	.000b
	Residual	115.368	2001	.058		
	Total	211.300	2006			

The results of the ANOVA analysis showed that the regression model had an F value of 332.777 with a significance level of 0.000 ($p < 0.05$), which indicates that the model as a whole is significant. The Sum of Regression Squares value of 95.932 indicates variations in extreme poverty levels that can be explained by five independent variables, while the Total Residual Squares of 115.368 represent variations not explained by the model. Therefore, the variables of health insurance, total income, housing ownership, education level, and type of employment simultaneously have a significant influence on extreme poverty rates. The results of the correlation analysis between poverty status and independent variables of the study. This analysis aims to look at the direction, strength, and significance of the relationship between each variable and poverty level. The resulting coefficient values provide an initial overview of variables that have the potential to have a strong influence on the regression model. The correlations data can be seen in the Table 4.

Table 4. Correlations

		STATUS_KEMISKINAN	KEPEMILIKAN_RUMAH	JENIS_PEKERJAAN	JUMLAH_PENGHASILAN	TINGKAT_PENDIDIKAN	JAMINAN_KESEHATAN
Pearson Correlation	STATUS_KEMISKINAN	1.000	-.253	-.505	-.505	-.267	-.211
	KEPEMILIKAN_RUMAH	-.253	1.000	-.001	.036	-.113	-.024
	JENIS_PEKERJAAN	-.505	-.001	1.000	.560	.208	.023
	JUMLAH_PENGHASILAN	-.505	.036	.560	1.000	.214	.000
	TINGKAT_PENDIDIKAN	-.267	-.113	.208	.214	1.000	.049
	JAMINAN_KESEHATAN	-.211	-.024	.023	.000	.049	1.000
Sig. (1-tailed)	STATUS_KEMISKINAN	.	.000	.000	.000	.000	.000
	KEPEMILIKAN_RUMAH	.000	.	.483	.051	.000	.145
	JENIS_PEKERJAAN	.000	.483	.	.000	.000	.154
	JUMLAH_PENGHASILAN	.000	.051	.000	.	.000	.497
	TINGKAT_PENDIDIKAN	.000	.000	.000	.000	.	.014
	JAMINAN_KESEHATAN	.000	.145	.154	.497	.014	.
N	STATUS_KEMISKINAN	2007	2007	2007	2007	2007	2007
	KEPEMILIKAN_RUMAH	2007	2007	2007	2007	2007	2007
	JENIS_PEKERJAAN	2007	2007	2007	2007	2007	2007
	JUMLAH_PENGHASILAN	2007	2007	2007	2007	2007	2007
	TINGKAT_PENDIDIKAN	2007	2007	2007	2007	2007	2007
	JAMINAN_KESEHATAN	2007	2007	2007	2007	2007	2007

The relationship between STATUS_KEMISKINAN variables and independent variables. The results of the Pearson Correlation analysis showed that each variable showed a negative correlation to poverty status, with the highest relationship strength in JUMLAH_PENGHASILAN (r = -0.505) and JENIS_PEKERJAAN (r = -0.505), followed by TINGKAT_PENDIDIKAN (r = -0.267), KEPEMILIKAN_RUMAH (r = -0.253), and JAMINAN_KESEHATAN (r = -0.211). The significance of the value (Sig. 1-tailed) < 0.05 for all of these variables indicates that the correlation exists statistically significant, meaning that an increase in these variables is likely to be accompanied by a decrease in poverty rates. The coefficients data can be seen in the Table 5.

Table 5. Coefficients

		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
Type		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Share	Tolerance	VIVID
1	(Constant)	1.909	.030		63.821	.000	1.850	1.967					
	KEPEMILIKAN_RUMAH	-.069	.004	-.266	-15.975	.000	-.077	-.060	-.253	-.336	-.264	.983	1.017
	JENIS_PEKERJAAN	-.143	.009	-.304	-15.171	.000	-.161	-.124	-.505	-.321	-.251	.678	1.475
	JUMLAH_PENGHASILAN	-.119	.008	-.291	-14.444	.000	-.135	-.103	-.505	-.307	-.239	.674	1.484
	TINGKAT_PENDIDIKAN	-.076	.008	-.162	-9.416	.000	-.092	-.060	-.267	-.206	-.156	.927	1.079
	JAMINAN_KESEHATAN	-.086	.007	-.203	-12.260	.000	-.099	-.072	-.211	-.264	-.203	.997	1.003

The coeficiens table showed that all independent variables had a negative and significant effect on poverty status ($p < 0.001$). The variable with the largest influence based on the Beta value was the type of job (-0.304), followed by the amount of income (-0.291), home ownership (-0.266), health insurance (-0.203), and education level (-0.162). The tolerance values and VIF values of all variables are at safe limits (VIF < 10), so there is no problem of multicollinearity. This indicates that each variable makes a unique contribution to the model and is worthy of use for further analysis. The coefficients correlations data can be seen in the Table 6.

Table 6. Coefficient Correlations

Type			JAMINAN_KESEHATAN	JUMLAH_PENGHASILAN	KEPEMILIKAN_RUMAH	TINGKAT_PENDIDIKAN	JENIS_PEKERJAAN
1	Correlations	JAMINAN_KESEHATAN	1.000	.020	.017	-.045	-.022
		JUMLAH_PENGHASILAN	.020	1.000	-.059	-.128	-.539
		KEPEMILIKAN_RUMAH	.017	-.059	1.000	.120	.012
		TINGKAT_PENDIDIKAN	-.045	-.128	.120	1.000	-.105

	JENIS_PEKERJAAN	-.022	-.539	.012	-.105	1.000
Covariances	JAMINAN_KESEHATAN	4.871E-5	1.160E-6	5.190E-7	-2.556E-6	-1.445E-6
	JUMLAH_PENGHASILAN	1.160E-6	6.778E-5	-2.088E-6	-8.512E-6	-4.171E-5
	KEPEMILIKAN_RUMAH	5.190E-7	-2.088E-6	1.846E-5	4.186E-6	4.918E-7
	TINGKAT_PENDIDIKAN	-2.556E-6	-8.512E-6	4.186E-6	6.538E-5	-7.982E-6
	JENIS_PEKERJAAN	-1.445E-6	-4.171E-5	4.918E-7	-7.982E-6	8.828E-5

Table 8 shows the covariance matrix and correlation among the independent variables in the model, namely Health Insurance, Total Income, Home Ownership, Education Level, and Type of Occupation. A relatively small correlation (near 0) indicates that the relationship between variables tends to be weak, with negative correlations such as Total Income and Type of Work (-0.539) indicating a moderately moderate inverse relationship. Meanwhile, the very small covariance value (near zero) confirms that a shift in one variable does not affect the other much in return, so the multicollinearity problem in this model is unlikely

The frequency distribution of each research variable is presented in the form of a bar chart. This visualization aims to provide a preliminary overview of the distribution of data in each category of variables. Can be seen in the Figure 3.

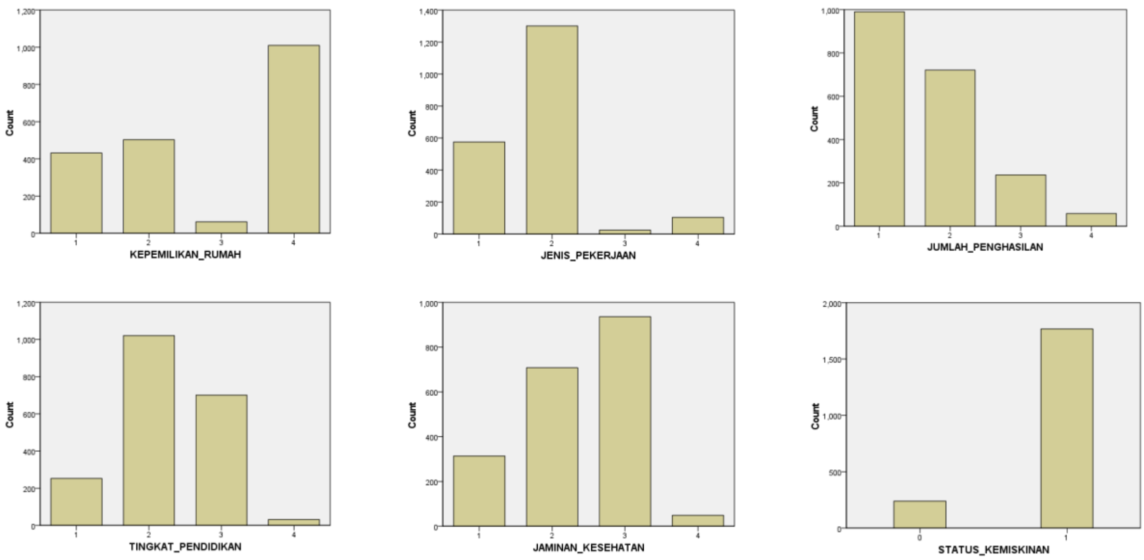

Figure 3. Variable Frequency Distribution Graph

The graph shows the frequency distribution for each research variable. In the KEPEMILIKAN_RUMAH variable, the majority of respondents were in category 4, while category 3 was the least. The JENIS_PEKERJAAN variable is dominated by category 2, while category 3 is very few. JUMLAH_PENGHASILAN the most in category 1, and the least in category 4. For TINGKAT_PENDIDIKAN, category 2 is the most, while category 4 is the least. The JAMINAN_KESEHATAN variable is the most in category 3, while category 4 is the least. Finally, STATUS_KEMISKINAN showed that most respondents were in category 1 (poor), with few respondents in category 0 (not poor).

4. Conclusions

The results of multiple linear regression analysis showed that the model built had a good performance in predicting poverty status. The value of the determination coefficient (R^2) of 0.454 indicates that 45.4% of the change in poverty status can be explained by the combination of variables of home ownership, type of occupation, total income, education level, and health insurance. Meanwhile, the remaining 54.6% were influenced by other factors that were not included in this study model. A similar Adjusted R^2 value (0.453) indicates that the model is quite stable with no signs of overfitting.

The results of the F test showed a value of 332.777 with a significance level of < 0.001, which indicates that all five independent variables have a significant effect simultaneously on poverty status. In other words, the model as a whole can provide a significant explanation for the variation in dependent variables.

The t-test for each regression coefficient showed that all independent variables had a negative and partially significant influence ($p < 0.05$). Among the five variables, type of job ($\beta = -0.304$) and amount of income ($\beta = -0.291$) had the greatest impact on reducing the likelihood of poverty status, followed by home ownership, health insurance, and education level.

In addition, the Standard Error of the Estimate (SEE) value of 0.240 indicates that the model's prediction error to the actual value can be considered relatively small. This confirms the conclusion that the model has a fairly satisfactory level of accuracy. Overall, the results of this study show that improvements in the aspects of employment, income, property ownership, education, and access to health insurance can contribute significantly to reducing poverty rates, so this model is relevant to be used as a basis for analysis and decision-making related to poverty alleviation.

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