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Evaluating Different K Values in K-Fold Cross Validation for Binary Logistic Regression to Classify Poverty

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ABSTRACT

Data mining is essential for decision-makers to efficiently analyze and extract insights from data. Classification is one of the data mining techniques used to organize data based on its features, helping to identify patterns and make predictions. This study evaluates Binary Logistic Regression (BLR), a generalized linear model suitable for binary outcomes, for classifying poverty depth across Indonesian regencies/cities in 2022, focusing on the impact of different K values in K-Fold cross-validation. The dataset includes 514 regencies/cities, with the Poverty Depth Index as the target variable, categorized into high (1) and low (0) levels, using 11 predictor variables. K-Fold Cross Validation was performed with K values of 3, 5, and 10, using accuracy and Area Under Curve (AUC) as evaluation metrics. The mean accuracy values for BLR are 75.7% for K=3, 74.3% for K=5, and 75.1% for K=10. Results show that K=3 offers the highest accuracy in classifying poverty depth in Indonesia, with the lowest standard deviation of 0.03. However, K=10 demonstrates superior discriminative ability in BLR, reflected by a higher AUC value. This study highlights the significant influence of K values in K-Fold cross-validation on BLR performance.

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A. INTRODUCTION

Information is vital today, yet extracting meaningful insights from the ever-expanding masses of data has become increasingly challenging. Asriningtias & Mardhiyah (2014) state that data mining has emerged as a crucial field that aids decision-makers in analyzing large datasets to uncover key information. This process involves the application of statistical and mathematical methods to identify patterns and trends (Larose & Larose, 2014).

Classification is a widely used technique in data mining that involves grouping data into classes or categories based on specific features. This approach helps reveal hidden patterns and enables predictions based on available information (Larose & Larose, 2014). One commonly used method for classification tasks is Binary Logistic Regression (BLR). Machine Learning (ML) plays a significant role in data mining, utilizing supervised learning algorithms such as BLR to develop accurate models for predicting new data labels based on trained data. ML is widely applied across various sectors, with models becoming increasingly sophisticated and capable of addressing complex problems as they process larger datasets (Agarwal & Das, 2020).

Accuracy is a crucial metric for assessing the precision of classification predictions in machine learning. The proportion of training and testing data significantly influences the accuracy level. The k-fold cross-validation method is a widely used technique for determining the optimal proportion of training and testing data, thereby improving accuracy, particularly for datasets with large sample sizes (Wong, 2015).

Several studies have employed the k-fold cross-validation method to optimize training and test data proportions and enhance classification accuracy. Sasongko (2016) applied this method to compare the performance of the Support Vector Machine (SVM) and Particle Swarm Optimization (PSO)-SVM algorithms in classifying high school interest tracks. Ling et al. (2019) utilized k-fold cross-validation to evaluate the accuracy of SVM, Artificial Neural Networks (ANN), and decision tree algorithms in analyzing concrete strength degradation in complex marine environments. Braun et al. (2020) applied this method to predict coronary heart disease using an ANN algorithm.

Furthermore, Tougui et al. (2021) implemented k-fold cross-validation to compare the performance of SVM and random forest algorithms in classifying Parkinson's disease. Putri et al. (2023) used k-fold cross-validation to compare error prediction in classification based on Chi-squared automatic interaction detection for balanced data. Prusty et al. (2024) analyzed the performance of SVM, random forest, k-nearest neighbors, and extreme gradient boosting in classifying risk factors for cervical cancer using this method. Meanwhile, other studies by Widodo et al. (2022), Asysyifa et al. (2023), and Azis (2024) have applied k-fold cross-validation in BLR models.

According to World Bank (2022), Indonesia, an archipelagic nation, had a population of 275.501 million in 2022, making it the fourth most populous country in the world. High population density often leads to various socio-economic challenges, including poverty and income inequality. Development efforts aim to alleviate poverty and reduce economic disparity to enhance overall well-being. Higher poverty levels are associated with lower community well-being, making population welfare a key factor in poverty assessments. Sahputra et al. (2023) define poverty as the inability to maintain a minimally acceptable standard of living, which is crucial for evaluating household well-being. Increasing poverty rates result in diminished community well-being and higher unemployment levels. Therefore, understanding the depth of poverty in each regency or city in Indonesia is essential for developing effective solutions. A system for classifying poverty depth across Indonesian regions is necessary (Hendayanti & Nurhidayati, 2020).

Previous research on BLR for poverty classification in Indonesia has provided valuable insights. Hendayanti & Nurhidayati (2020) evaluated the performance of BLR in classifying poverty and identifying factors influencing the Poverty Depth Index across Indonesian provinces in 2019. Their study achieved a prediction accuracy of 85.3%, highlighting the significance of variables such as average years of schooling and expected years of schooling. Similarly, Nurrizqi et al. (2022) analyzed poverty levels in Indonesia in 2021 using BLR, reporting an accuracy of 83.33%, with the Human Development Index (HDI) and Gini Ratio identified as key variables. Despite Indonesia's vast and diverse population, understanding poverty at the regency or city level remains crucial for targeted policy interventions. This study employs BLR to classify poverty depth levels across Indonesia, aiming to identify the most effective strategies for addressing and mitigating poverty.

B. RESEARCH METHOD

1. Binary Logistic Regression (BLR)

Regression is a data analysis technique that explains the link between a response variable and one or more predictor variables, according to Hosmer et al. (2013). the link between predictor factors and a categorical response variable is examined using logistic regression. There are several types of it, including Multinomial Logistic Regression (MLR), Ordinal Logistic Regression (OLR), and Binary Logistic Regression (BLR). In BLR, a binary response to the variable with two categories is explicitly used, whereas, in OLR and MLR, ordinal data scales and multiple-category nominal scales are used (Agresti, 2018). The responding variable (Y) for each observation follows a Bernoulli distribution, with the probability distribution function given as follows:

$$f(y_i, \pi) = \pi^{y}(1-\pi)^{1-y_i},\ i = 1, 2, \ldots, n \tag{1}$$

In a random sample with $Y_1, Y_2, \ldots, Y_n$ follow a Bernoulli distribution with parameter π, the BLR model can be expressed in Equation (2).

$$\pi(x_i) = \frac{\exp\left(\beta_0 + \beta_1 X_{1i} + \ldots + \beta_q X_{qn}\right)}{1 + \exp\left(\beta_0 + \beta_1 X_{1i} + \ldots + \beta_q X_{qn}\right)} \tag{2}$$

where:

$\pi(x_i)$	:	Probability of success as an outcome, given the input vector x_i
β_0	:	Intercept term in logistic regression model
$\beta_1, \beta_2, \ldots, \beta_q$	:	The regression coefficients associated with each predictor $X_1, X_2, \ldots, X_q$
$X_{1i}, X_{2i}, \ldots, X_{qn}$	:	The predictor variables for the i-th observation

The correlation between some or all predictor variables is referred to as multicollinearity. Similar to linear regression models, logistic regression models are likewise sensitive to multicollinearity, according to Hosmer et al. (2013). Strong reliance between two or more predictor variables is indicated by high multicollinearity. The Variance Inflation Factor (VIF), which is computed using the following formula, can be used to evaluate multicollinearity:

$$VIF = \frac{1}{1 - R_p^2},\ p = 1, 2, \ldots, q \tag{3}$$

where R_p^2 is the coefficient of determination for the p-th predictor variable, and q is the number of predictor variables.

2. K-Fold Cross Validation

Popular validation technique K-Fold Cross Validation works effectively in situations when there is limited information. Subsets of the data are created during this procedure, and each subset has an equal amount of observations. The data is used for testing and training in turn in K-Fold Cross Validation. The procedure is run K times, using K-1 subsets for training and one subset for testing in each iteration. According to Arisandi et al. (2022), the usual values for K are 3, 5, and 10.

3. Data and Research Variable

The analysis uses secondary data on Indonesian poverty indicators for the year 2022, broken down by regency or city, from the Badan Pusat Statistik's official website. The response variable in the dataset, which consists of 514 regencies/cities, represents how the Poverty Depth Index is classified according to its national average. Eleven predictor variables are used in the analysis, as shown in Table 1 below.

Table 1. Research Variable

Variable	Description
X_1	Average Years of Schooling
X_2	Adjusted Per Capita Expenditure
X_3	Expected Years of Schooling
X_4	Open Unemployment Rate
X_5	Labor Force Participation Rate
X_6	Percentage of Population with BPJS Health Coverage Receiving Contribution Assistance
X_7	Percentage of Households with Access to Adequate Sanitation
X_8	Percentage of Households with Access to Adequate Water Sources
X_9	Adjusted Per Capita Gross Regional Domestic Product (GRDP)
X_{10}	Gross Regional Domestic Product (GRDP) at Current Prices Distribution
X_{11}	Gross Regional Domestic Product (GRDP) at Current Prices

4. Analysis Step

The analysis steps for this research are illustrated in the flowchart shown in Figure 1.

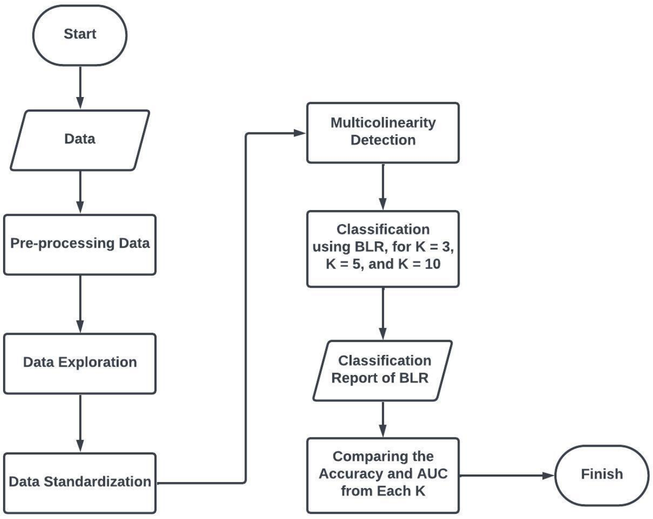


Figure 1. Effects of selecting different switching under dynamic conditions

The following description provides an analysis of Figure 1, which illustrates the data used in this study:

1. Data preprocessing: Convert the Poverty Depth Index (PDI) from numeric form into categorical form. Begin by calculating the average value of the PDI across all regions and cities. Each region or city is then categorized based on this average value: if the PDI is less than or equal to the average PDI, it is classified as "low;" if the PDI is greater than the average PDI, it is classified as "high."
2. Data exploration: Perform data exploration using descriptive statistics by creating a spatial map and pie chart for the response variable. Additionally, calculate the mean, median, standard deviation, maximum, and minimum values for the predictor variables.
3. Data standardization: Data standardization transforms predictor variables to a common scale to enhance model performance. This involves calculating the mean and standard deviation for each variable and applying the z-score formula:

$$z = \frac{(x - \mu)}{\sigma} \tag{4}$$

   This process scales each variable to have a mean of 0 and a standard deviation of 1, ensuring consistency across different variables (Prasetyo, 2012).
4. Multicollinearity detection: According to Hosmer et al. (2013), logistic regression models are also sensitive to collinearity, similar to linear regression models. High collinearity indicates a strong dependence between two or more predictor variables. Detection of multicollinearity can be performed by calculating the Variance Inflation Factor (VIF) using Equation (3).
5. Classification using BLR for K = 3, K = 5, and K = 10.
6. K-Fold Cross Validation evaluation: The purpose of performance measurement in classification is to evaluate how well the classifier can classify data. This performance measurement uses a table known as a confusion matrix or cross-tabulation (Liu, 2019).

Table 2. Confusion Matrix

		Predicted	
		0	**1**
Actual	**0**	True Positive (TP)	False Positive (FP)
	1	False Negative (FN)	True Negative (TN)

The machine learning classifier was evaluated based on prediction accuracy and Area Under the Curve (AUC), which can be obtained using the following equations (Nti et al., 2021).

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{5}$$

$$AUC = \int_0^1 \frac{TP}{(TP + FN)} d\frac{FP}{(FP + TN)} = \int_0^1 \frac{TP}{P} d\frac{FP}{N} \tag{6}$$

Beyond accuracy, several additional measurements provide more insight and help mitigate the effects of class imbalance. These measurements include:

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

$$Specificity = \frac{TN}{TN + FP} \tag{8}$$

$$Recall = \frac{TP}{TP + FN} \tag{9}$$

$$F1 - Call = 2 \times \left(\frac{Precision \times Recall}{Precision + Recall}\right) \tag{10}$$

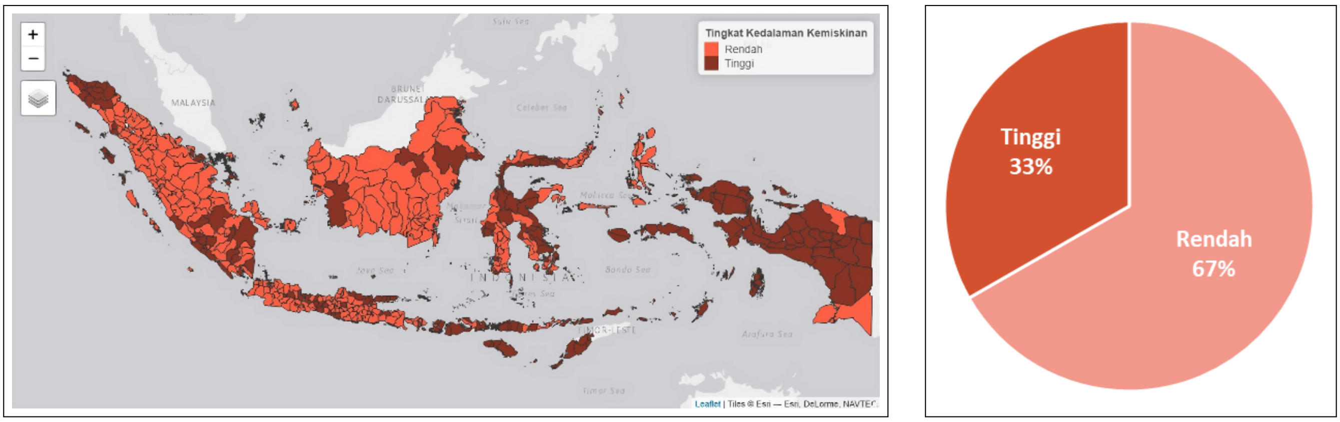
7. Conclusion.

C. RESULT AND DISCUSSION

This section outlines the research findings, highlighting BLR's performance in classifying poverty depth in Indonesia. The analysis examines various K values in K-Fold cross-validation and their influence on model accuracy and discriminative ability.

1. Descriptive Statistics

Before performing data analysis, it's important to examine the characteristics of the data used in the study. Descriptive statistics are divided into two parts: one for the categorical response variable and the other for the eleven numeric predictor variables.



(a) (b)

Figure 2. (a) Distribution of Poverty Depth Levels in Indonesia 2022, (b) Percentage of Poverty Depth Levels in Indonesia

The map of the distribution of poverty depth categories by regency/city in Indonesia for 2022 can be seen in Figure 2. It shows that the number of regencies/cities with low poverty depth is greater compared to those with high poverty depth. High poverty depth regencies/cities are present on every island and tend to be more concentrated in the eastern regions of Indonesia. Descriptive statistics on the predictor variables can be seen in Table 3 below.

Table 3. Descriptive Statistics of Predictor Variables

Variable	Average	Standard Deviation	Minimum	Maximum
X_1	8.55	1.62	1.58	13.03
X_2	10,644.95	2,752.59	4.190.00	24,221.00
X_3	13.09	1.31	4.07	17.81
X_4	4.57	2.32	0.09	11.82
X_5	69.97	6.71	56.37	97.53
X_6	47.89	19.53	0.08	98.88
X_7	77.15	18.43	2.13	98.77
X_8	86.47	14.54	0.19	100.00
X_9	65,639.25	78,622.25	6,264.00	831,798.00
X_{10}	6.62	7.64	0.15	64.05
X_{11}	37,290.14	81,061.51	256.00	794,936.00

2. Data Standardization

Table 4 displays the outcome of data standardization using Z-Score.

Table 4. Standardized Data

Regency/City	X_1	X_2	X_3	$\cdots$	X_{11}
Simeulue	0.73	-1.19	0.76	$\cdots$	-0.43
Aceh Singkil	0.08	-0.60	0.96	$\cdots$	-0.42
Aceh Selatan	0.21	-0.83	1.23	$\cdots$	-0.38
Aceh Tenggara	0.84	-0.88	0.90	$\cdots$	-0.39
Aceh Timur	-0.14	-0.55	-0.02	$\cdots$	-0.30
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$
Kota Jayapura	1.97	1.65	1.49	$\cdots$	-0.02

3. Multicollinearity Detection

One way to discover multicollinearity is by examining the VIF value. The outcome of figuring out the VIF value for every variable is as follows.

Table 5. VIF Value for Multicollinearity Detection

Predictor Variables	VIF
X_1	2.60
X_2	1.80
X_3	2.44
X_4	1.70
X_5	1.44
X_6	1.39
X_7	1.56
X_8	1.27
X_9	1.68
X_{10}	1.95
X_{11}	1.76

Table 5 indicates that there is no multicollinearity between the variables because each variable has a VIF value of less than 10. As a result, all predictor variables can be used to classify poverty depth levels in Indonesia in 2022 using BLR.

4. Classification using BLR

The training and testing processes were carried out using K-Fold Cross Validation, sequentially with K = 3, K = 5, and K = 10. Each training and testing iteration produced classification metrics. The results are presented in Tables 6, 7, and 8.

Table 6. Classification Report of BLR for 3-Fold Cross Validation

Fold	Accuracy	AUC
1	0.713	0.800
2	**0.789**	**0.832**
3	0.767	0.799
Mean	**0.757**	**0.810**
Std. Deviation	**0.039**	**0.019**

Based on Table 6, the highest accuracy was achieved in testing the second fold, which also produced the highest AUC value. This indicates that the model developed for the second fold was able to correctly classify poverty depth levels in Indonesian regencies/cities for the year 2022 with an accuracy of 78.9%. Additionally, the model tested on the second fold demonstrated a discrimination capability of 83.2%, effectively distinguishing between low and high poverty levels.

Table 7. Classification Report of BLR for 5-Fold Cross Validation

Fold	Accuracy	AUC
1	0.755	0.825
2	0.767	**0.857**
3	0.757	0.822
4	**0.786**	0.840
5	0.650	0.724
Mean	**0.743**	**0.814**
Std. Deviation	**0.053**	**0.052**

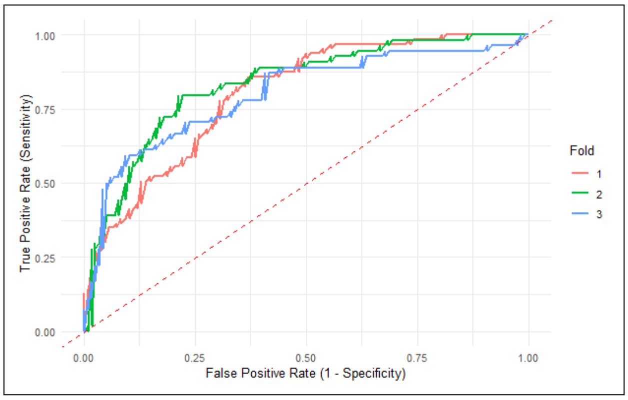
Based on Table 7, the highest accuracy was achieved in testing the fourth fold, while the model that produced the highest AUC value was from the second fold. This indicates that the model developed for the fourth fold was able to accurately classify poverty depth levels in Indonesian regencies/cities for the year 2022 with an accuracy of 78.6%. However, the model tested on the second fold demonstrated superior discrimination capability compared to the fourth fold model, with an ability to correctly differentiate between low and high poverty levels at 85.7%.

Table 8. Classification Report of BLR for 10-Fold Cross Validation

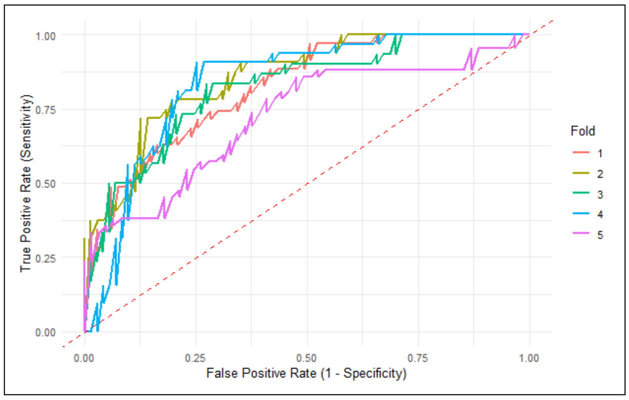
Fold	Accuracy	AUC
1	0.784	0.848
2	**0.846**	**0.921**
3	0.692	0.794
4	0.765	0.905
5	0.686	0.711
6	0.765	0.810
7	0.706	0.784
8	0.846	0.848
9	0.765	0.797
10	0.654	0.747
Mean	**0.751**	**0.816**
Std. Deviation	**0.066**	**0.066**

Based on Table 8, the highest accuracy was achieved in testing the second fold, which also produced the highest AUC value. This indicates that the model developed for the second fold was able to accurately classify poverty depth levels in Indonesian regencies/cities for the year 2022 with an accuracy of 84.6%. Additionally, the model tested on the second fold demonstrated a discrimination capability of 92.1%, effectively distinguishing between low and high poverty levels.

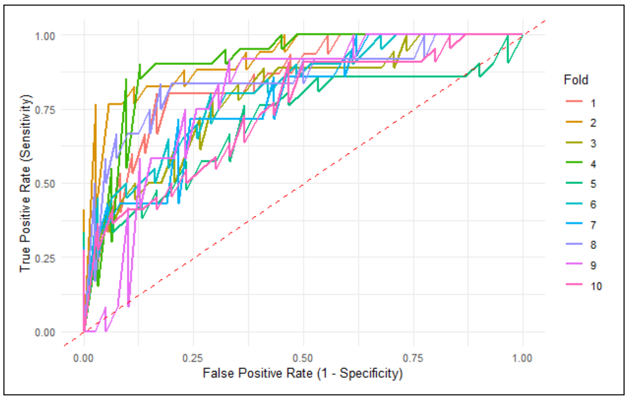
The results of this research are consistent with previous studies that use BLR to classify poverty in Indonesia. Hendayanti & Nurhidayati (2020) achieved an accuracy of 85.3%, while Nurrizqi et al. (2022) reported 83.3%. Both studies identified key socio-economic factors affecting poverty classification. However, unlike these studies, which focused on the national level, this research examines poverty depth at the regional level. The findings support BLR as a reliable method for poverty classification and highlight how different K values in K-Fold cross-validation affect prediction accuracy.



(a)



(b)



(c)

Figure 3. (a) ROC Curves of 3-Fold Cross Validation, (b) ROC Curves of 5-Fold Cross Validation, (c) ROC Curves of 10-Fold Cross Validation

Based on Figure 3, the linear line represents the boundary of the model's ability to differentiate between class levels in classification. Figure 3 indicates that each testing process in the Cross-Validation demonstrates that the model has effective discriminative power in distinguishing between low and high levels of poverty depth. This is also supported by Tables 6, 7, and 8, where the AUC values obtained are greater than 0.5, indicating that the model has good discriminative ability.

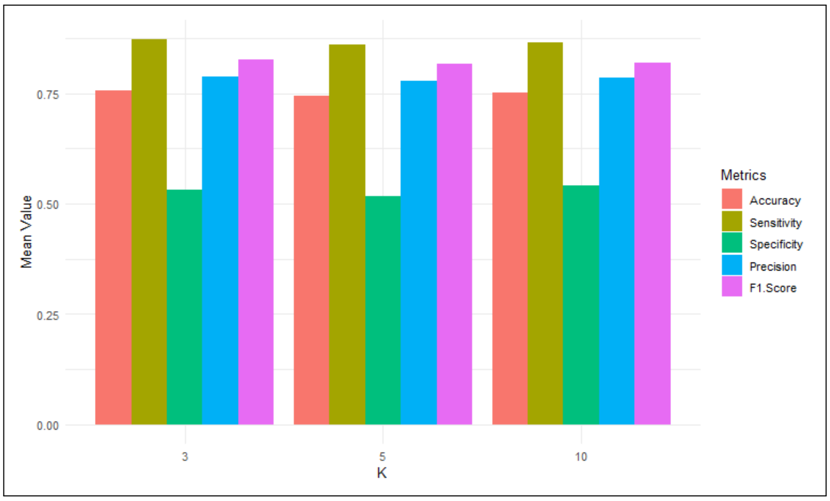


Figure 4. Effects of selecting different switching under dynamic condition

Figure 4 shows that the K-Fold Cross Validation experiments for K = 3, K = 5, and K = 10 yield classification metrics with average values that are not significantly different from each other. However, when evaluating the model's ability to predict poverty depth levels in Indonesia for 2022, the use of K = 3 proves to be more effective compared to K = 5 and K = 10. This is because it achieves the highest average accuracy and has the lowest standard deviation compared to the standard deviations for K = 5 and K = 10.

D. CONCLUSION AND SUGGESTION

The application of BLR for classifying poverty depth in Indonesia for 2022, using K-Fold Cross Validation, shows that the model can accurately classify data. The mean accuracy values obtained for K = 3, K = 5, and K = 10 were 75.7%, 74.3%, and 75.1%, respectively. This indicates that using K = 3 provides the most accurate classification of poverty depth in Indonesia for 2022, with the lowest standard deviation of 0.03. However, using K = 10 reveals that the BLR model has superior discriminative ability, as evidenced by a higher AUC value compared to K = 3 and K = 5.

To enhance the classification of poverty depth levels in Indonesia, it's beneficial to compare BLR with a Support Vector Machine (SVM) using K-fold cross-validation with K = 3, 5, and 10. This comparison will help determine the optimal K for each model. Addressing data imbalance is also crucial, and employing techniques like Synthetic Minority Over-sampling Technique (SMOTE) can improve model robustness by generating synthetic samples for underrepresented classes. Comparing SVM and BLR, alongside exploring ANN and data balancing methods, will provide a comprehensive evaluation and potentially lead to better results in classifying poverty depth levels.

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AUTHOR CONTIBUTION

Julia: Writing-original draft preparation, writing-reviewing and editing. M. Fathurahman: Conceptualization, methodology. Sri Wahyuningsih: Data curation. Memi Nor Hayati: Investigation, supervision. Surya Prangga: Software, validation. All authors have read and agreed to the published version of the article.

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The authors declare no conflict of interest.

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