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A Computatioal Analysis of Kernel-Based Nonparametric Regression Applied to Poverty Data

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Abstract
Poverty remains one of the most persistent challenges affecting regional development, particularly in less-developed areas such as Nusa Tenggara Timur Province, Indonesia. The multidimensional nature of poverty is intricately linked to various socioeconomic factors, making its analysis and prediction a complex task. This research aims to model the relationship between poverty and socioeconomic variables in Nusa Tenggara Timur Province, Indonesia. The purpose of the study is to assess the effectiveness of nonparametric regression, specifically using kernel methods, to provide a more accurate representation of the complex and nonlinear relationships between predictor variables and poverty levels. The study focuses on several key variables, including average years of schooling, labor force participation rate, percentage of households with access to electricity, population density, illiteracy rate, and life expectancy. The research utilized a kernel regression approach, comparing the performance of different kernel functions, including Gaussian, Epanechnikov, Triangle, and Quartic kernels. The model's performance was evaluated using metrics such as Mean Squared Error (MSE), Generalized Cross Validation (GCV), and the coefficient of determination (R^2). The results showed that the Gaussian kernel function provided the most accurate predictions for poverty levels, with the best balance between model complexity and error.

Keywords: Kernel regression; Nonparametric Regression; Poverty; Computation; NTT

Abstrak
Kemiskinan menjadi salah satu tantangan paling persisten yang memengaruhi pembangunan daerah, terutama di daerah tertinggal seperti Provinsi Nusa Tenggara Timur, Indonesia. Sifat multidimensi kemiskinan terkait erat dengan berbagai faktor sosial ekonomi, sehingga analisis dan prediksinya menjadi tugas yang kompleks. Penelitian ini bertujuan untuk memodelkan hubungan antara kemiskinan dan variabel sosial ekonomi di Provinsi Nusa Tenggara Timur, Indonesia. Tujuan dari studi ini adalah untuk menilai efektivitas regresi nonparametrik, khususnya menggunakan metode kernel, untuk memberikan representasi yang lebih akurat terhadap hubungan yang kompleks dan nonlinier antara variabel prediktor dan tingkat kemiskinan. Penelitian ini berfokus pada beberapa variabel kunci, termasuk rata-rata lama

sekolah, tingkat partisipasi angkatan kerja, persentase rumah tangga yang memiliki akses ke listrik, kepadatan penduduk, tingkat buta huruf, dan harapan hidup. Penelitian ini menggunakan pendekatan regresi kernel, membandingkan kinerja berbagai fungsi kernel, termasuk kernel Gaussian, Epanechnikov, Segitiga, dan Quartik. Kinerja model dievaluasi menggunakan metrik seperti Mean Squared Error (MSE), Generalized Cross Validation (GCV), dan koefisien determinasi (R^2). Hasil penelitian menunjukkan bahwa fungsi kernel Gaussian memberikan prediksi yang paling akurat untuk tingkat kemiskinan, dengan keseimbangan terbaik antara kompleksitas model dan kesalahan.

Kata Kunci: Regresi Kernel; Regresi Nonparametrik; Kemiskinan; Komputasi; NTT

1. INTRODUCTION

Poverty is a complex multidimensional issue and remains a major development challenge in Indonesia (Sugiharti et al., 2023), particularly in regions with limited resources such as Nusa Tenggara Timur Province (NTT) (BPS, 2024). According to data from the Central Bureau of Statistics (BPS) of NTT in 2023, the poverty rate in this region was recorded at 20.6 percent, significantly higher than the national average of 9.4 percent. NTT consists of more than 600 islands with challenging geographical conditions, which affect resource distribution, access to infrastructure, and unequal provision of basic services. This indicates that communities in this province still face difficulties in meeting basic needs such as education, health, and household lighting.

The poverty phenomenon is not caused by a single factor but is the result of interactions among various social, economic, and geographical aspects (Usmanova et al., 2022). Several dominant factors suspected to contribute to the high poverty rate include the low average years of schooling, a still-high illiteracy rate, relatively low life expectancy, population density, low labor force participation, and limited access to household lighting infrastructure(Rahmawati et al., 2021a). These variables represent aspects of education, health, demographics, and infrastructure, all of which are interrelated and play a role in shaping the socioeconomic conditions of the community(Ciucu et al., 2025; Usmanova et al., 2022; Wang et al., 2022). Therefore, rather than merely understanding the correlations among these factors, a more appropriate approach is to model the pattern of relationships between these variables, enabling more accurate predictions of poverty levels, which in turn can support efforts to mitigate poverty in the region(Puttanapong et al., 2022).

So far, poverty modeling has generally used parametric approaches such as linear regression, which assumes a linear relationship between predictor and response variables. However, the relationship between socio-economic factors and poverty is often nonlinear and cannot be fully explained by rigid parametric models. This highlights the need for more flexible and adaptive methods to capture the complex relationship patterns in the data (Hardle, 1994; Widyastuti et al., 2021). One promising approach is nonparametric regression, a method that does not require assumptions about specific functional forms between variables (Dani et al., 2021; Ratnasari et al., 2021). The main advantages of nonparametric regression include its flexibility in capturing previously unknown relationship forms, its ability to handle data with nonlinear and heterogeneous patterns, and its independence from specific distributional assumptions such as residual normality (Aydin & Yilmaz, 2021; Chen, 1991; Mariati et al., 2020). Therefore, this method is highly suitable for poverty conditions in NTT, which are determined by many factors with complex and nonlinear relationships.

In this study, the kernel regression approach is used as a modeling solution with strong flexibility (Bukhtoyarov & Tynchenko, 2021; Masrur Ahmed et al., 2022; Seo et al., 2025). Kernel regression estimates the value of the response variable based on observations around the estimation point using weights determined by the kernel function (Adrianingsih et al., 2021; Hidayat et al., 2019; Linke et al., 2022). The kernel function plays an important role in defining the estimation pattern (Rahmawati et al., 2021b). Several commonly used kernel functions that will be compared in this study include the Gaussian kernel, Epanechnikov kernel, Triangle kernel, and Quartic kernel(Asfirah et al., 2025; Marques et al., 2020). Each kernel function has its own mathematical characteristics in assigning weights to data around the prediction point, and their performance may vary depending on the data pattern(Ali, 2022; Ameer Basheer et al., 2020). This study's novel contribution lies in conducting a comprehensive computational comparison of multiple kernel functions to identify the estimator that most faithfully captures the intricate relationship between socioeconomic indicators and poverty levels in Nusa Tenggara Timur Province. By integrating advanced kernel-selection strategies with Generalized Cross-Validation, the research not only refines poverty–predictor modeling but also establishes a methodological framework for kernel choice in nonparametric analysis of development data.

2. METHODS

2.2 Kernel Nonparametric Regression

Kernel nonparametric regression is one of the commonly used approaches due to its highly flexible form and relatively simple mathematical computation(Hidayat et al., 2019). Its purpose is to capture nonlinear relationships between the response and predictor variables. In this method, the smoothing process is emphasized, making it highly dependent on the kernel function and bandwidth(Adrianingsih et al., 2021; Linke et al., 2022). The kernel weights are determined by the kernel function (K), which includes several types such as Uniform, Triangle, Gaussian, Epanechnikov, Quadratic, Triweight, and Cosine kernels(Rahmawati et al., 2021b). The weights are influenced by the bandwidth or smoothing parameter b. In general, the kernel function (K) with bandwith b is defined in Equation 1.

$$K_b(a) = \frac{1}{b} K\left(\frac{a}{b}\right) \tag{1}$$

The regression curve is a curve with an unknown pattern, and there is no prior information regarding the nature of the relationship. Subsequently, the regression curve $f(x_i)$ can be approximated using a kernel estimator.

$$f_b(x) = n^{-1} \sum_{i=1}^{n} \frac{K_b(x - x_i)}{n^{-1} \sum_{i=1}^{n} K_b(x - x_i)} y_i = n^{-1} \sum_{i=1}^{n} W_{bi}(x)\, y_i \tag{2}$$

where $K_b(x - x_i)$ is the kernel function:

$$K_b(x - x_i) = \frac{1}{b} K\left(\frac{x - x_i}{b}\right) \tag{3}$$

and $W_{bi}(x)$ is the weighting function.

$$W_{bi}(x) = \sum_{i=1}^{n} \frac{K_b(x - x_i)}{n^{-1} \sum_{i=1}^{n} K_b(x - x_i)} \tag{4}$$

Equation (4) shows that $\hat{f}_b(x)$ depends on the kernel function K and the bandwidth parameter b. Several types of kernel functions are presented in Table 1.

Table 1. Kernel Function

Name	Kernel	Name	Kernel
Uniform	$\frac{1}{2}; I_{[-1,1]}(x)$	Quadrat	$\frac{15}{16}(1 - 2x^2 + x^4); I_{[-1,1]}(x)$
Triangle	$(1 - \lvert x \rvert); I_{[-1,1]}(x)$	Triweight	$\frac{35}{32}(1 - 3x^2 + 3x^4 - x^6); I_{[-1,1]}(x)$
Gaussian	$\frac{1}{\sqrt{2\pi}} exp\left(-\frac{1}{2}x^2\right); I_{[-\infty,\infty]}(x)$	Cosinus	$\frac{\pi}{4} cos\left(\frac{\pi}{2}x\right); I_{[-1,1]}(x)$
Epanechnikov	$\frac{3}{4}(1 - x^2); I_{[-1,1]}(x)$		

The criterion for selecting a good kernel function is based on the minimum kernel risk that can be obtained from the optimal kernel. The kernel has a smoothing parameter or bandwidth, denoted by b, which controls the degree of influence of data points in determining the location, emphasizing the balance between bias and variance. One technique for estimating the kernel regression function is by using the Nadaraya-Watson estimator.

$$\widehat{m}(X) = \frac{\sum_{i=1}^{n} K_b(x_i - x) Y_i}{\sum_{i=1}^{n} K_b(x_i - x)} \tag{6}$$

2.3 Evaluation Metrics

In this study, there are three main metrics used to evaluate the performance of the kernel regression model, namely:

a. **Generalized Cross-Validation (GCV)**

GCV is the primary metric used as a benchmark in nonparametric regression modeling. It is used to evaluate model performance by considering the balance between the level of prediction error and model complexity. The formula for GCV is presented in Equation (7).

$$GCV = \frac{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\left\{\frac{1}{n} tr\,(\boldsymbol{I} - \boldsymbol{S})\right\}^2} \tag{7}$$

Where:

$\boldsymbol{I}$: Identity matrix

$\boldsymbol{S}$: Hat matrix

$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$

b. **Coefficient of Determination (R^2)**

The coefficient of determination measures how much of the data variation can be explained by the model. The formula for R^2 is presented in Equation (8).

$$R^2 = \left(1 - \frac{SSE}{SST}\right) \times 100\% \tag{8}$$

Where:

$$SSE = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \ ; \ SST = \sum_{i=1}^{n}(y_i - \bar{y})^2 \tag{9}$$

2.4 Data, Data Sources, and Research Variables

The data used in this study are secondary data obtained from the Central Bureau of Statistics of Nusa Tenggara Timur Province in 2023. The sampling technique employed is purposive sampling, taking into account data availability and recency. The variables used consist of response and predictor variables, as presented in Table 2.

Table 2. Variables in the Study

Variable	Notation	Operational Definition
Percentage of the Poor Population	Y	The percentage of the population living below the poverty line relative to the total population of a region.
Average Years of Schooling	X_1	The average number of years spent in formal education by individuals aged 25 and over.

Variable	Notation	Operational Definition
Life Expectancy	X_2	The estimated average lifespan a person is expected to reach from birth.
Illiteracy Rate of Population Aged 15 and Over	X_3	The proportion of the population aged 15 and over who are unable to read and write simple sentences in any language, relative to the total population aged 15 and over.
Population Density	X_4	The number of people per unit area (per square kilometer), reflecting the population density of a region.
Labor Force Participation Rate	X_5	The percentage of the working-age population (typically aged 15 and over) actively engaged in economic activities (working or seeking work), relative to the total working-age population.
Percentage of Households with Access to Electricity	X_6	The percentage of households with access to adequate sources of lighting (e.g., electricity) relative to the total number of households in a region.

2.4 Research Stages

The research stages are outlined in four main steps, namely data pre-processing, data exploration, kernel nonparametric regression modeling, and model comparison evaluation.

1. Creating boxplots for each numeric variable, accompanied by indicators of minimum, maximum, and average values; and constructing scatter plots between predictor variables and the response variable to observe initial relationship patterns.
2. Constructing a simultaneous bandwidth grid scheme with 50 test points in each predictor dimension based on the range from minimum to maximum values. Applying four types of kernel functions: Gaussian, Epanechnikov, Triangle, and Quartic;
3. Calculating predicted response values using the average kernel function for each bandwidth combination. Computing the Mean Squared Error (MSE) and Generalized Cross Validation (GCV) for each bandwidth combination;
4. Determining the optimal bandwidth combination based on the smallest GCV value;
5. Creating a radar chart to visualize the performance of each kernel based on GCV, MSE, and R^2 values.

All stages of this research were implemented using R software, with the following library packages: ggplot2, dplyr, reshape2, tidyr, gridExtra for data visualization and manipulation; fmsb for radar charts; pracma and MASS for mathematical function support.

3. Result and Discussion

3.1 Data Exploration

An initial exploration of the data was conducted to understand the basic characteristics of each variable, both the response and predictor variables. The visualizations used include box plots and bar charts, which serve to identify data distribution, the presence of outliers, and to compare the minimum, maximum, median, and mean values across variables. The box plot is shown in Figure 1.

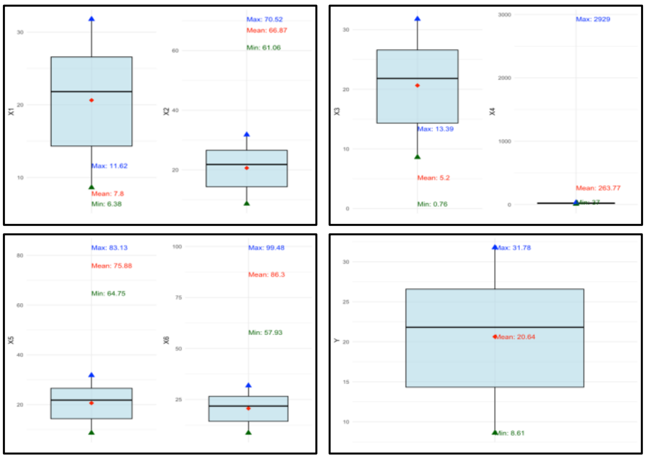

Figure 1. Box Plot for Each Variable

The box plots for variables X_1 through X_6 and Y show varying distributions across the variables. Variables such as X_4 exhibit a very large value range (with a maximum of 2929 and a much smaller mean of 263.77), indicating the presence of extreme outliers that dominate the distribution. Meanwhile, variables like X_2, X_5, and X_6 display narrower and more symmetrical distributions, suggesting a more concentrated spread without prominent outliers. The median values are generally close to the means, except in the case of X_4 where there is a significant gap. For the response variable Y, the distribution is symmetrical, with a maximum value of 31.78 and a minimum of 8.61, and a mean of 20.64. This indicates that most Y values lie near the center of the range without extreme deviations.

3.2 Scatter Plot

One effective way to identify patterns or relationships is using scatter plots. Scatter plots allow us to observe the data distribution and potential correlations between each predictor variable and the response variable. The following figure (Figure 3) presents the scatter plot of each predictor variable (X1 to X6) against the percentage of poor people, providing an initial insight into whether there are any linear relationships or clear patterns among these variables.

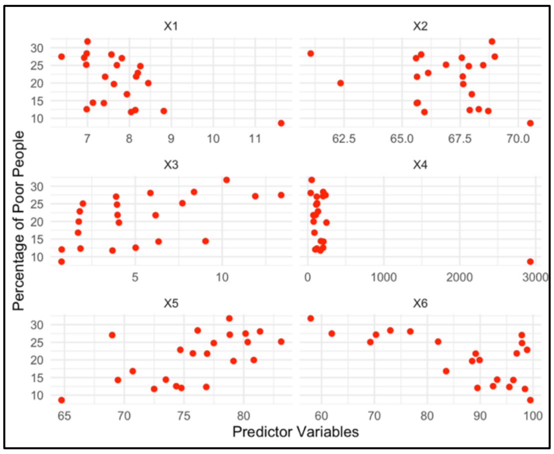

Figure 3. Scatter Plot of Each Predictor Variable with the Response

Based on the scatter plots between the percentage of the poor population and each predictor variable (X1 to X6) in Figure 3, it appears that the pattern of relationships between variables is irregular or random and does not form a clear pattern. Several variables show widespread data distribution and do not follow a particular direction, indicating that the linear regression approach may be less appropriate. Therefore, this study uses a nonparametric regression method because it is more flexible in capturing complex patterns of relationships between variables. To estimate this model, a kernel function will be used as a smoothing approach that does not assume a particular relationship between the predictor and response variables.

3.3 Comparison of Kernel Function

The following table presents a comparison of the four types of kernel functions used in this study. The comparison includes the values of Generalized Cross Validation (GCV), Mean Squared Error (MSE), the coefficient of determination (R^2), as well as the optimal bandwidth for each predictor variable. Table 3 aims to demonstrate the performance of each kernel in modeling poverty data in Nusa Tenggara Timur.

Table 3. Comparison Table of the 4 Types of Kernel Functions

Kernel Function	GCV	MSE	R^2	Optimal Bandwidth					
				X_1	X_2	X_3	X_4	X_5	X_6
Gaussian	36.34053	7.070372	83.81198	0.434	0.057	0.104	0.057	0.953	0.953
Triangle	41.09018	3.128567	92.83697	0.953	0.010	0.340	0.529	0.764	0.340
Epanechnikov	41.33855	3.700606	91.52725	0.953	0.010	0.340	0.529	0.764	0.340
Quartic	41.29725	3.197834	92.67837	0.953	0.010	0.340	0.529	0.764	0.340

3.4 Best Model Selection

Based on the analysis of the three radar plots GCV, MSE, and R^2 displayed in Figure 4, the selection of the best kernel function in kernel-based nonparametric regression is determined by the lowest GCV value.

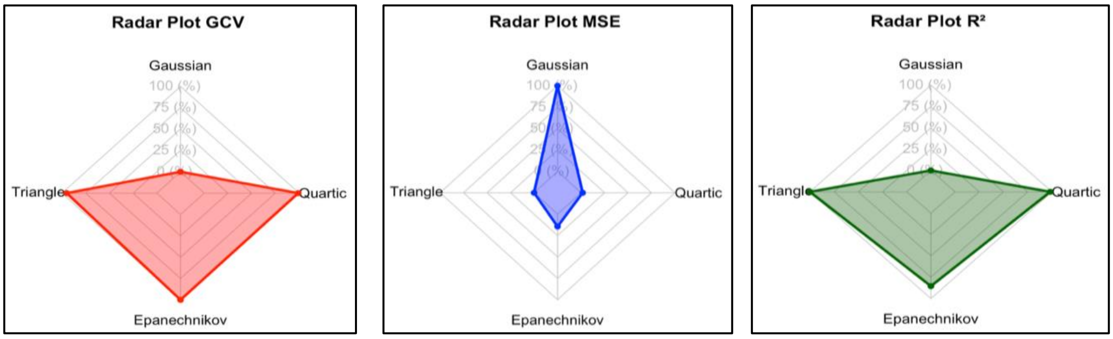

Figure 4. Radar Plot of GCV, MSE, and R^2

In the GCV radar plot, the Gaussian kernel function shows the lowest value compared to the other kernels, namely Quartic, Epanechnikov, and Triangle. Although the Gaussian kernel does not stand out in the MSE and R^2 radar plots, nonparametric regression prioritizes GCV, as it balances model complexity and error level, making it more suitable for evaluating nonparametric models. Therefore, it can be concluded that the Gaussian kernel function is the best choice in this study and visualized in Figure 5.

Based on these findings, the recommended mitigation measures include improving access to and the quality of education, strengthening healthcare services, empowering the workforce, and ensuring equitable development of basic infrastructure. This analysis highlights that the use of nonparametric regression with a Gaussian kernel provides an adaptive and accurate representation of the complex relationships between variables, making it a solid foundation for formulating more targeted poverty alleviation policies.

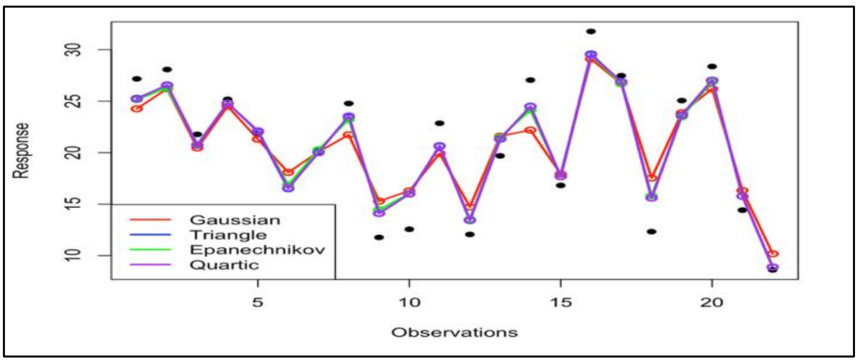

Figure 5. Comparison Plot of Prediction Results

Figure 5 shows a comparison of different kernel functions, Gaussian, Triangle, Epanechnikov, and Quartic used to smooth the data. The plot demonstrates how each kernel function affects the response variable, with the black dots representing the original observations. From the graph, it is evident that the Gaussian kernel (red line) provides the smoothest fit to the data, capturing the underlying trend while minimizing the influence of noise. This suggests that the Gaussian kernel is the most suitable choice for this study, offering the best balance between smoothness and accuracy in modeling the response variable.

4. Conclusion

In conclusion, the Gaussian kernel function demonstrates superior performance in modeling poverty data in Nusa Tenggara Timur, as evidenced by its lowest Generalized Cross Validation (GCV) value compared to the other kernel functions. While the MSE and R^2 values do not significantly favor the Gaussian kernel, the GCV metric, which balances model complexity and error, makes it the optimal choice for nonparametric regression in this study. The findings suggest that the Gaussian kernel effectively captures the complex and nonlinear relationships between predictor variables and poverty levels, providing a robust foundation for developing targeted poverty alleviation strategies.

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6. Future Research

Future research could explore spatial kernel regression to better capture geographic relationships, as location, infrastructure access, and proximity between regions significantly affect poverty. Incorporating spatial data into the model could improve its ability to handle non-linear relationships and provide more precise policy recommendations.

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