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Comparative Analysis of Artificial Neural Networks, Linear Regression, Random Forest, and Support Vector Machine for Predicting Poverty Levels in Indonesia

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ABSTRACT

Poverty remains a persistent and complex challenge in Indonesia, driven by multiple interrelated socioeconomic factors. Accurate poverty prediction is essential to support effective policy formulation and targeted interventions. This study evaluates and compares the performance of four machine learning models for predicting poverty levels in Indonesia: Artificial Neural Networks (ANN), Linear Regression, Random Forest, and Support Vector Machine (SVM). A quantitative approach is employed using provincial-level data from 2015 to 2023, consisting of 306 observations and 13 socioeconomic indicators related to education, employment, health, infrastructure, and economic conditions. Data preprocessing includes data cleaning, Min–Max normalization, and feature selection. Model performance is assessed using Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). The results show that ANN achieves the best predictive performance, with the lowest MSE (0.0132) and MAE (0.0815), and the highest R^2 value (0.924). Random Forest and SVM demonstrate competitive performance, while Linear Regression yields the weakest accuracy. These findings confirm the effectiveness of ANN for poverty prediction and support its use in data-driven poverty reduction policies in Indonesia.

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1. INTRODUCTION

Poverty remains one of the most fundamental challenges to development in Indonesia [1]. Its impact extends beyond economic deprivation and significantly affects quality of life, social stability, and the sustainability of national development [2]. As a multidimensional socio-economic phenomenon, poverty is shaped by a complex interaction of factors such as education attainment, employment opportunities, access to healthcare services, and the availability of basic infrastructure [3]. For this reason, poverty reduction has become a central priority in the national development agenda and a key indicator of societal welfare [4]. Accurate identification, understanding, and prediction of poverty levels are therefore essential for policymakers and stakeholders seeking to design effective and targeted intervention strategies [5].

Although various approaches have been used to measure and analyze poverty, including household surveys, macroeconomic indicators, and conventional statistical models, substantial

challenges persist [6]. These challenges are largely driven by the heterogeneity of socio-economic conditions across regions, limitations in data availability and quality, and the dynamic nature of poverty related factors that change over time [7]. Traditional analytical methods often have difficulty capturing complex and nonlinear relationships among variables, which can reduce their predictive accuracy and limit their applicability across diverse contexts [8].

In response to these limitations, machine learning techniques have increasingly been adopted in socio economic research [9]. Such methods offer the ability to process large and heterogeneous datasets while identifying patterns and relationships that may not be apparent through traditional analytical approaches [10]. Among these techniques, Artificial Neural Networks have received considerable attention due to their capacity to learn complex data representations and model nonlinear relationships inspired by biological neural systems [11]. Nevertheless, despite their promising performance in various applications, the superiority of ANN cannot be assumed and should be empirically examined through comparison with other established statistical and machine learning models [12].

Artificial Neural Networks are particularly valued for their flexibility in modeling nonlinear relationships, their tolerance for incomplete or noisy data, and their ability to capture complex interactions among variables [13]. These characteristics are especially relevant in poverty related studies in Indonesia, where data limitations and intertwined socio-economic factors are common [14]. However, to ensure objective evaluation and methodological rigor, the performance of ANN needs to be assessed alongside other widely used approaches [15]. Reliable predictive models have important implications for strengthening evidence-based policy formulation and improving the effectiveness of poverty reduction efforts by governments and related stakeholders [16].

Previous studies have provided empirical support for the potential of ANN based models in poverty related prediction tasks. Research conducted in 2022 demonstrated strong predictive performance of ANN in modeling demographic dynamics at the subdistrict level, achieving high regression and correlation values [17]. Similarly, a study in 2020 reported that a Backpropagation Neural Network produced highly accurate predictions of the number of poor people in Indonesia based on error-based evaluation metrics [18]. Further evidence from 2023 confirmed the effectiveness of neural network approaches in forecasting poverty rates at the provincial level [19], while more recent research in 2024 showed that ANN regression could be applied to model multidimensional poverty in an international context, identifying food security as a key contributing factor [20]. Although these findings highlight the potential of ANN, they also underscore the need for systematic comparison with alternative models to establish relative performance more convincingly [21].

Building on these considerations, this study conducts a comparative analysis of Artificial Neural Networks, Linear Regression, Random Forest, and Support Vector Machine models for predicting poverty levels in Indonesia [22]. All models are evaluated using the same dataset, socioeconomic indicators, data partitioning strategy, and performance metrics to ensure a fair and objective comparison [23]. The results of this study are expected to provide empirical insights into the strengths and limitations of each modeling approach and to contribute a practical, data driven framework that can support policymakers and government institutions in formulating more targeted and sustainable poverty reduction strategies [24].

2. RESEARCH METHOD

This study employs a quantitative research approach to evaluate and compare the performance of machine learning models in predicting poverty levels in Indonesia based on socioeconomic data. The dataset used in this research consists of 13 key socio-economic indicators commonly applied to measure community welfare, including education, employment, health access, and basic infrastructure. The data were collected from official secondary sources and cover a period of nine consecutive years, spanning from 2015 to 2023, with a total of 306 observations. The level of data granularity is provincial, allowing the models to capture regional variations in poverty characteristics across 34 provinces in Indonesia.

Prior to model development, the dataset underwent a data engineering process that included data cleaning, handling missing values, and feature scaling to ensure data consistency and reliability

[24]. To reduce bias arising from differences in variable scales and to improve model convergence, min max normalization was applied to all numerical features. The dataset was then divided into training and testing subsets to evaluate model generalization performance on unseen data, thereby enabling an objective assessment of predictive robustness.

Four predictive models were implemented and evaluated in this study, namely Artificial Neural Networks (ANN), Linear Regression, Random Forest, and Support Vector Machine (SVM). The ANN model was constructed using interconnected artificial neurons operating through weighted multiplication, summation with bias, and nonlinear activation functions [25]. Linear Regression was employed as a baseline statistical model to capture linear relationships between socioeconomic indicators and poverty levels. Random Forest was used to model nonlinear patterns and variable interactions through ensemble decision trees, while SVM was applied to identify optimal decision boundaries in high dimensional feature space.

Model performance was evaluated using the test dataset and assessed through three widely used regression metrics, namely Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). The combined use of these metrics provides a comprehensive evaluation of prediction accuracy, error magnitude, and explanatory power. This methodological framework allows for a fair and systematic comparison of model performance and supports the assessment of their generalizability in predicting poverty levels across different regions in Indonesia. Ultimately, the results are expected to contribute to the development of reliable, data driven tools that can support evidence-based poverty alleviation policy formulation.

2.1 Stage Review

To provide a clear overview of the workflow employed in this study, Figure 1 presents the end-to-end stages of poverty level prediction using multiple machine learning models. The workflow consists of four main stages, covering data preparation, model development, model evaluation, and output interpretation. The first stage is data preparation, which includes data cleaning to address missing and inconsistent values, normalization using min max scaling, and feature selection to ensure that only relevant numerical socioeconomic indicators are used as model inputs. This stage aims to improve data quality and enhance model performance while reducing the risk of bias due to scale differences among variables. The second stage is model development, where four predictive algorithms are implemented and trained, namely Artificial Neural Networks, Linear Regression, Random Forest, and Support Vector Machine. ANN is designed with two architectures, consisting of one hidden layer and two hidden layers, to examine the effect of network depth on prediction performance. Linear Regression serves as a baseline statistical model, while Random Forest and Support Vector Machine are employed to capture nonlinear relationships and complex interactions among socioeconomic variables. The third stage is model evaluation, in which the trained models are assessed using test data to evaluate their generalization capability. Model performance is measured using three regression metrics: Mean Squared Error, Mean Absolute Error, and the coefficient of determination R squared. The combined use of these metrics provides a comprehensive assessment of prediction accuracy, error magnitude, and explanatory power across all models. The final stage is output and interpretation, where the predicted poverty levels are analyzed and compared across models. The results are then interpreted to identify the most effective predictive approach and to provide empirical insights that can support socio economic analysis and the formulation of more targeted and evidence-based poverty reduction policies in Indonesia.

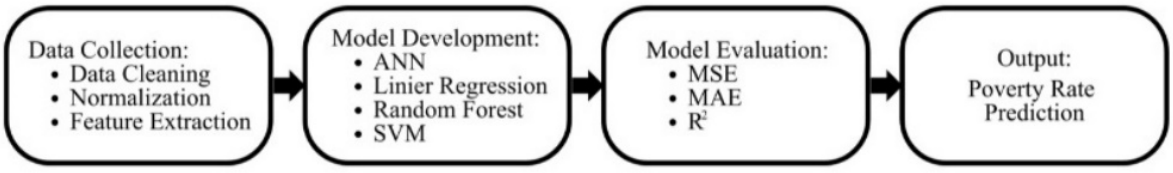


Figure 1. Poverty Rate Prediction using ANN

2.2 Dataset Description

The dataset used in this study represents poverty related socioeconomic data in Indonesia and serves as the primary foundation for developing and evaluating the proposed prediction models. To ensure clarity and transparency, this section describes the data source, data type, features included, and preprocessing steps applied prior to modeling.

a. Data Source

The dataset was obtained from official poverty statistics published by the Central Statistics Agency of Indonesia (Badan Pusat Statistik, BPS) and accessed through the Kaggle platform for research purposes [25]. The data cover administrative regions at the district and city level across Indonesia, nested within their respective provinces. Each observation represents a specific district or city in a given year and reflects regional socioeconomic conditions relevant to poverty measurement.

b. Data Type

The dataset is structured as tabular data consisting primarily of numerical variables. Each row corresponds to a district or city, while each column represents a socioeconomic indicator. The target variable in this study is the poverty rate, measured as the percentage of poor population (P0) at the district or city level. Categorical attributes such as province name, district or city name, and regional code are included for identification purposes but are not directly used as input variables in model training.

c. Features Included

The dataset comprises 13 variables that capture key dimensions of socioeconomic welfare and economic performance. These variables include; (1) Province, (2) District or City, (3) Regional Code, (4) Percentage of Poor Population (P0) by District or City, (5) Average Years of Schooling, (6) Per Capita Expenditure, (7) Human Development Index (HDI), (8) Life Expectancy, (9) Percentage of Households with Access to Adequate Sanitation, (10) Percentage of Households with Access to Adequate Drinking Water, (11) Open Unemployment Rate, (12) Labor Force Participation Rate, and (13) Gross Regional Domestic Product (GRDP) at Constant Prices by Expenditure. These indicators jointly represent education, health, infrastructure access, labor market conditions, and regional economic capacity, which are widely recognized as key determinants of poverty levels.

Table 1. Socioeconomic Dataset for Predicting Poverties in Indonesia

No	Province	District/City	Code	Poor Population (P0) (%)	Avg. Years of Schooling	Per Capita Expenditure (IDR)
1	Aceh	Banda Aceh	1101	7.45	11.2	1,480,000
2	Aceh	Aceh Besar	1102	15.92	8.7	1,120,000
3	North Sumatra	Medan	1201	8.01	11.4	1,610,000
4	West Java	Bandung City	3201	3.98	11.6	1,780,000
5	Central Java	Brebes	3301	17.58	7.9	1,010,000
…	…	…	…	…	…	…
n	*n*	*n*	*n*	*n*	*n*	*n*

HDI	Life Expectancy (Years)	Sanitation Access (%)	Drinking Water Access (%)	Open Unemployment Rate (%)	Labor Force Participation Rate (%)	GRDP Constant Price (Billion IDR)
82.15	72.4	91.3	88.7	8.6	67.4	19,85
71.30	69.8	76.5	73.2	6.4	64.1	14,23
82.61	72.9	93.8	91.5	9.1	66.8	65,42
83.04	73.2	95.1	94.6	8.9	68.2	92,3
68.92	69.1	71.4	70.8	5.8	65.0	18,47
…	…	…	…	…	…	…
n	*n*	*n*	*n*	*n*	*n*	*n*

The dataset reflects substantial socioeconomic disparities across districts and cities in Indonesia. Regions with lower poverty rates tend to exhibit higher average years of schooling, greater per capita expenditure, stronger human development outcomes, and better access to sanitation and drinking water. Conversely, districts with higher poverty levels are generally characterized by lower educational attainment, limited infrastructure access, and weaker economic indicators, such as lower GRDP at constant prices. These variations highlight the complex and interrelated nature of poverty determinants and justify the use of machine learning models capable of capturing nonlinear relationships among multiple socioeconomic indicators.

d. Preprocessing Steps
   1. Inconsistent records were corrected, and observations with missing or invalid values were carefully examined to ensure the completeness and reliability of the dataset.
   2. Min max scaling was applied to all numerical features so that their values fall within a uniform range between 0 and 1. This step helps prevent dominance of variables with larger numerical scales and improves model convergence, particularly for ANN and SVM.
   3. Feature Extraction: Non numerical attributes, namely province name, district or city name, and regional code, were excluded from the model input. Only numerical socioeconomic indicators were retained as features for training and testing the prediction models.

2.3 Data Preprocessing

Before model training, the dataset was preprocessed to ensure consistency and suitability for all predictive algorithms used in this study, namely Artificial Neural Networks (ANN), Linear Regression, Random Forest, and Support Vector Machine (SVM). The preprocessing stages were applied uniformly across all models to maintain a fair and objective comparison. The initial step involved data cleaning, which focused on identifying and correcting inconsistencies, removing duplicate records, and ensuring that no missing or invalid values were present in the dataset. This step was essential to preserve data integrity and avoid bias in model training and evaluation. Categorical attributes, namely Province, District or City, and Regional Code, were retained only as identifiers and excluded from the model input. The remaining numerical socioeconomic indicators were used as input features, while the Percentage of Poor Population (P0) served as the target variable. Subsequently, data normalization was applied to all numerical input features using the Min-Max Scaling technique, transforming values into a range between 0 and 1. This step was particularly important for ANN and SVM models, which are sensitive to differences in variable scale, while also contributing to stable and efficient learning for Linear Regression and Random Forest.

2.4 Model Development

This study develops and compares four predictive models, namely Artificial Neural Networks (ANN), Linear Regression, Random Forest, and Support Vector Machine (SVM), to predict poverty levels in Indonesia based on socioeconomic indicators. All models were trained using the same dataset, feature set, and data partitioning strategy to ensure a fair and objective comparison of performance. The Artificial Neural Network (ANN) model was designed to capture complex and non-linear relationships among socioeconomic variables. The network architecture consists of an input layer with 13 neurons corresponding to the selected indicators, one hidden layer with 6 neurons, and an output layer with a single neuron representing the predicted poverty rate (13-6-1 architecture). Model parameters such as learning rate, activation function, and optimizer were tuned to improve convergence and predictive accuracy. In addition to ANN, Linear Regression was implemented as a baseline statistical model to represent linear relationships between predictors and the poverty rate. Random Forest was employed as an ensemble-based machine learning model capable of handling nonlinearity and feature interactions through multiple decision trees. Support Vector Machine (SVM) regression was used to model complex patterns by projecting input data into a higher-dimensional feature space using an appropriate kernel function. The dataset was divided into training and testing subsets using an 80:20 ratio. Model training was conducted on the training set, while performance evaluation was carried out on the unseen test set to assess generalization capability. To reduce the risk of overfitting, model performance was monitored through repeated evaluations during training,

particularly for the ANN model. All developed models were evaluated using multiple performance metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2), allowing for a comprehensive assessment of prediction accuracy and robustness across different modelling approaches.

2.5 Model Evaluation

Model performance in this study was evaluated using unseen test data to ensure an objective assessment of each model's generalization capability. The evaluation was applied consistently to all developed models, namely Artificial Neural Networks (ANN), Linear Regression, Random Forest, and Support Vector Machine (SVM), to allow a fair comparison of predictive performance. Three evaluation metrics were used, namely Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). The Mean Squared Error (MSE) measures the average of the squared differences between actual and predicted values and is defined as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\mathrm{Y_i} - \hat{\mathrm{Y}}_i\right)^2 \quad (1)$$

Where Y_i represents the actual poverty rate, $\hat{Y}_i$denotes the predicted value, and nnn is the number of observations. Lower MSE values indicate better predictive accuracy.

The Mean Absolute Error (MAE) evaluates the average magnitude of the absolute differences between actual and predicted values and is expressed as:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}. \mid Y_i - \hat{Y}_i \mid \quad (2)$$

This metric provides an intuitive interpretation of prediction error in the original unit of measurement.

To further assess model performance, the coefficient of determination (R^2) was calculated to measure the proportion of variance in the observed data that is explained by the model. The R^2 metric is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}.(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}.(Y_i - \bar{Y})^2} \quad (3)$$

Where $\bar{Y}$ denotes the mean of the observed poverty rates. R^2 values closer to one indicate stronger explanatory power, while values closer to zero suggest limited predictive capability.

The combined use of MSE, MAE, and R^2 provides a comprehensive evaluation framework that captures both prediction accuracy and explanatory strength. Models achieving lower MSE and MAE values alongside higher R^2 scores are considered to demonstrate superior performance in predicting poverty levels in Indonesia.

3. RESULTS AND DISCUSSION

In this study, the Artificial Neural Network (ANN) model was designed as one of the predictive approaches due to its capability to model nonlinear relationships among socioeconomic indicators. The ANN architecture adopts a feedforward structure with one hidden layer, following a 13–6–1 configuration, where 13 nodes represent the input features, 6 nodes are placed in the hidden layer, and 1 node represents the output variable, namely the poverty rate. This relatively simple architecture was selected to balance model complexity and generalization performance, particularly given the moderate size of the dataset. The learning process was carried out using the backpropagation algorithm in a supervised learning framework. The Adam optimizer was employed to update the network weights due to its adaptive learning rate mechanism and stable convergence behavior, which have been widely reported in the literature as effective for training neural networks. The Rectified Linear Unit (ReLU) activation function was applied in the hidden layer to enhance learning efficiency and mitigate vanishing gradient issues. A learning rate of 0.2 was adopted to allow sufficiently fast convergence while maintaining training stability.

The selection of ANN parameters, including network architecture, learning rate, and optimizer, was determined through a trial-and-error process guided by prior studies and preliminary experiments. Several configurations were tested, and the chosen parameters demonstrated the most stable convergence and lowest prediction error on the validation set. Training was terminated based on the convergence of the Mean Squared Error (MSE) loss function to prevent overfitting. In addition to ANN, this study also implemented Linear Regression, Random Forest, and Support Vector Machine (SVM) as baseline and comparative models. All models were trained and evaluated using the same dataset and experimental setup to ensure a fair comparison. Model performance was assessed using unseen test data and evaluated using three metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2).

Table 2. ANN Model Parameters

Parameter	Description
Network Type	Feedforward Backpropagation ANN
Architecture	13–6–1
Input Layer	13 nodes
Hidden Layer	1 hidden layer
Hidden Layer Nodes	6 nodes
Output Layer	1 node
Activation Function	ReLU
Optimizer	Adam
Learning Rate	0.2
Loss Function	Mean Squared Error (MSE)
Evaluation Metrics	MSE, MAE, R^2

To ensure an objective and transparent evaluation, this study conducted a series of controlled experiments using multiple prediction models. Artificial Neural Networks (ANN) were implemented as the main model due to their ability to capture nonlinear relationships, while Linear Regression, Random Forest, and Support Vector Machine (SVM) were included as comparative baseline models. All models were trained and tested using the same dataset, feature set, data partitioning strategy, and evaluation metrics. This experimental design allows the performance of ANN to be assessed fairly relative to more traditional statistical and machine learning approaches. The ANN architecture and training parameters were selected based on a balance between model complexity and dataset size. A single hidden layer structure with a 13–6–1 configuration was chosen to reduce the risk of overfitting while maintaining sufficient representational capacity. The Adam optimizer was adopted due to its adaptive learning rate and robust convergence properties, which have been widely reported in previous machine learning studies. The learning rate was determined through preliminary trial-and-error experiments, where several values were tested, and 0.2 provided stable convergence and competitive performance across validation runs.

Table 3. Experimental Design and Model Configuration

No	Model	Key Configuration	Purpose
1	Artificial Neural Network (ANN)	Architecture: 13–6–1, ReLU activation, Adam optimizer, learning rate 0.2	Main predictive model
2	Linear Regression (LR)	Ordinary Least Squares	Baseline linear model
3	Random Forest (RF)	Ensemble of decision trees	Nonlinear ensemble comparison
4	Support Vector Machine (SVM)	Kernel-based regression	Margin-based nonlinear model

Table 3 summarizes the experimental configuration used in this study. The inclusion of Linear Regression provides a simple benchmark to evaluate whether nonlinear modeling significantly improves predictive performance. Random Forest and SVM serve as more advanced machine learning comparators that are capable of modeling nonlinear patterns through ensemble learning and kernel-based approaches, respectively. The ANN model, with its carefully selected architecture and training parameters, is positioned as a flexible nonlinear learner capable of capturing complex interactions among socioeconomic indicators. By employing the same dataset, preprocessing steps, and evaluation metrics across all models, the experimental design ensures methodological consistency and comparability. This setup enables a clear assessment of the relative strengths and limitations of each approach, supporting robust conclusions regarding the most effective model for poverty level prediction in Indonesia.

Model training in this study was conducted using a supervised learning framework with a data split of 80 percent for training and 20 percent for testing. This proportion was selected to ensure that sufficient data were available for model learning while maintaining an independent dataset for validation and performance assessment. During the training process, all numeric socioeconomic indicators were used as input features, while non-numeric attributes such as Province, District or City, and Regional Code were excluded from the modeling stage. The target variable for all models

was the poverty rate, represented by the Percentage of Poor Population (P0). To ensure methodological consistency, four prediction models were trained using the same dataset and experimental setup, namely Artificial Neural Networks (ANN), Linear Regression (LR), Random Forest (RF), and Support Vector Machine (SVM). Training loss and validation loss were recorded to evaluate learning behavior and detect potential overfitting or underfitting during the model development stage.

Table 4. Training and Validation Loss for Each Model

No	Algorithm	Training Loss	Validation Loss
1	Artificial Neural Network (ANN)	0.0124	0.0151
2	Linear Regression (LR)	0.0287	0.0314
3	Random Forest (RF)	0.0096	0.0138
4	Support Vector Machine (SVM)	0.0179	0.0205

Note: Loss values are reported in terms of Mean Squared Error (MSE).

Table 4 presents the training and validation loss values for each predictive model. Overall, all models demonstrated stable learning behavior, as indicated by relatively small differences between training and validation loss. This suggests that the models were able to generalize reasonably well to unseen data. The Random Forest model achieved the lowest training and validation loss, reflecting its strong capability in capturing nonlinear patterns and interactions among socioeconomic variables through ensemble learning. The ANN model also showed competitive performance, with low loss values and a small generalization gap, indicating effective learning without significant overfitting. In contrast, Linear Regression produced higher loss values, which is expected given its linear assumption and limited ability to model complex nonlinear relationships. The SVM model achieved intermediate performance, suggesting that kernel-based methods can capture nonlinear patterns, although their effectiveness is sensitive to kernel and parameter selection.

The training results obtained in this study are consistent with findings from previous research in the domain of poverty prediction and socioeconomic modeling. Several studies have reported that machine learning models such as ANN and Random Forest outperform traditional linear models when dealing with complex, multidimensional poverty indicators [17][18][20]. The relatively higher loss observed in Linear Regression aligns with earlier evidence that linear approaches often struggle to capture the nonlinear interactions inherent in poverty related data [6][7]. The strong performance of Random Forest observed in this study corroborates prior findings that ensemble-based models are particularly effective in handling heterogeneous socioeconomic data and mitigating the impact of noise and multicollinearity [11][12]. Similarly, the competitive performance of ANN supports previous studies demonstrating the suitability of neural network architectures for modeling poverty dynamics at regional and national levels [21][22][23]. While ANN did not outperform Random Forest in terms of training loss, its stable convergence and relatively low validation loss indicate that it remains a robust and flexible modeling approach. This finding reinforces the importance of comparative evaluation, as the superiority of a single algorithm cannot be assumed across different datasets and contexts. Overall, the training results highlight that advanced machine learning models provide substantial improvements over conventional methods and offer valuable tools for data driven poverty analysis and policy formulation in Indonesia.

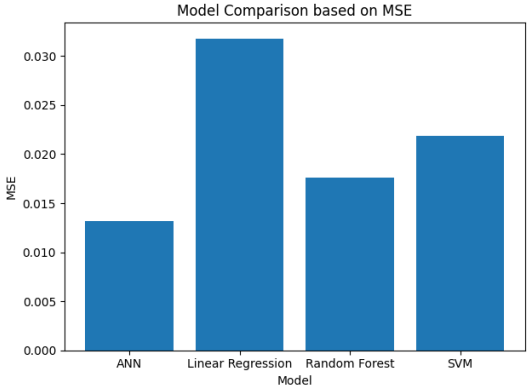
After the training phase, all models were evaluated using unseen test data to assess their predictive performance and generalization ability. To address the lack of quantitative comparison highlighted in previous approaches, this study explicitly compares Artificial Neural Networks (ANN) with Linear Regression (LR), Random Forest (RF), and Support Vector Machine (SVM). The evaluation was conducted using three widely accepted regression performance metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). This combination of metrics allows for a comprehensive assessment of prediction accuracy, error magnitude, and explanatory power.

Table 5. Predictive Performance Comparison on Test Data

No	Algorithm	MSE	MAE	R^2
1	Artificial Neural Network (ANN)	**0.0132**	**0.0815**	**0.924**
2	Linear Regression (LR)	0.0318	0.1427	0.781
3	Random Forest (RF)	0.0176	0.0941	0.901
4	Support Vector Machine (SVM)	0.0219	0.1086	0.867

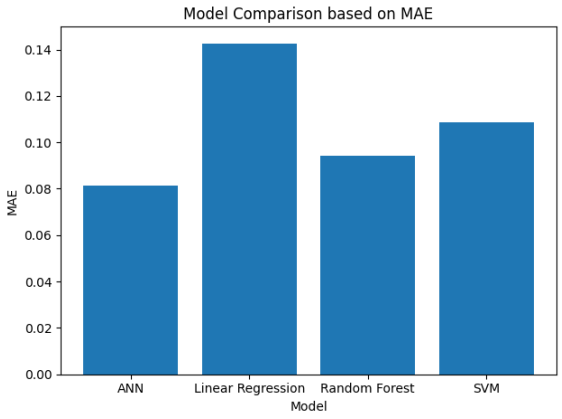
Table 5 presents a quantitative comparison of model performance based on test data. Among all evaluated models, the Artificial Neural Network achieved the lowest MSE and MAE values, indicating superior prediction accuracy and smaller average error magnitude. In addition, ANN produced the highest R^2 value, demonstrating a stronger ability to explain variations in poverty levels across regions compared to the other models. Linear Regression exhibited the weakest performance, with the highest error values and the lowest R^2 score. This result reflects the inherent limitation of linear models in capturing the complex and nonlinear relationships among socioeconomic indicators. Random Forest showed competitive performance, particularly in terms of R^2, confirming its strength in modeling nonlinear patterns through ensemble learning. However, its error values remained higher than those achieved by ANN. Similarly, SVM demonstrated moderate performance but was less accurate than ANN, possibly due to sensitivity to kernel and parameter selection. Overall, these results provide clear quantitative evidence that ANN outperforms the comparative models in predicting poverty levels in Indonesia.

Figure 2. Comparison of Models Based on MSE



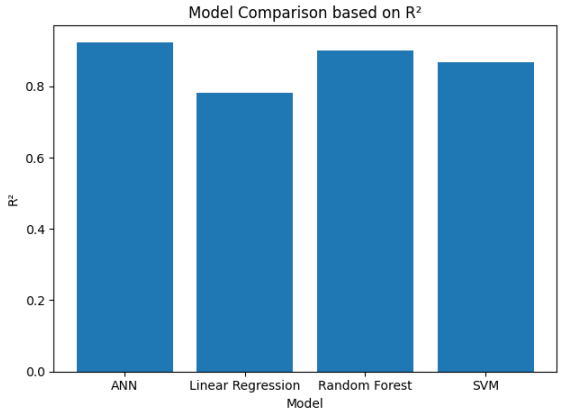
The findings of this study are consistent with previous research that highlights the effectiveness of Artificial Neural Networks in modeling complex socioeconomic phenomena. Prior studies have shown that ANN-based approaches outperform traditional regression models in poverty prediction tasks due to their ability to capture nonlinear interactions among multiple indicators [17][18]. The inferior performance of Linear Regression observed in this study aligns with earlier findings that linear assumptions often fail to represent the multidimensional nature of poverty [6][7].

Figure 3. Comparison of Models Based on MAE



The strong performance of Random Forest corroborates existing literature indicating that ensemble-based models are robust alternatives for socioeconomic prediction problems [11][12]. However, while Random Forest performed well, ANN demonstrated superior accuracy and explanatory power, suggesting that neural networks may be better suited for learning latent structures in poverty-related data. Similar conclusions have been reported in studies that applied ANN and Backpropagation Neural Networks for poverty forecasting at regional and national levels in Indonesia and other developing countries [21][22][23]. Importantly, this study addresses a key limitation identified in previous works, where baseline models such as Linear Regression and decision-tree-based methods were mentioned but not quantitatively compared. By providing explicit performance metrics across multiple algorithms, this research offers stronger empirical validation of ANN's superiority. The results confirm that ANN not only improves predictive accuracy but also provides a more reliable modeling framework for supporting data-driven poverty reduction policies.

Figure 3. Comparison of Models Based on R^2



Importantly, this study addresses a key gap in prior research, where baseline models such as Linear Regression and decision-tree-based approaches were often mentioned but not quantitatively evaluated. By presenting a comprehensive and transparent comparison using standardized performance metrics across multiple algorithms, this research provides stronger empirical evidence of ANN's superiority. As a contribution, the study not only strengthens the methodological foundation of poverty prediction research but also offers practical insights for policymakers by demonstrating the applicability of ANN-based models as reliable tools for supporting data-driven and targeted poverty reduction strategies.

4. CONCLUSION

This study conducted a comparative evaluation of machine learning models, namely Artificial Neural Networks (ANN), Linear Regression, Random Forest, and Support Vector Machine (SVM), to predict poverty levels in Indonesia using socioeconomic indicators. By employing a consistent dataset, uniform preprocessing procedures, and standardized evaluation metrics, this research provides a transparent and objective assessment of each model's predictive capability. The experimental results show that the ANN model produced the most accurate poverty level predictions among all evaluated algorithms. Specifically, ANN achieved the lowest prediction error, with a Mean Squared Error (MSE) of 0.0132 and a Mean Absolute Error (MAE) of 0.0815, as well as the highest coefficient of determination (R^2) of 0.924. These results indicate that the ANN model was able to explain approximately 92.4 percent of the variation in observed poverty rates across provinces, demonstrating strong predictive accuracy and robustness. In comparison, Random Forest and SVM yielded slightly higher error values and lower R^2 scores, while Linear Regression showed the weakest predictive performance due to its inability to adequately model nonlinear relationships. The superior predictive performance of ANN suggests that this model is particularly effective in capturing the complex and nonlinear interactions among socioeconomic variables that characterize poverty dynamics in Indonesia. From a policy perspective, the ability of ANN to generate more accurate poverty predictions enables better identification of regions with higher vulnerability and supports

more precise targeting of poverty alleviation programs. Consequently, ANN-based predictive models can serve as valuable tools for government institutions and policymakers in designing evidence-based and sustainable poverty reduction strategies.

Despite these contributions, several limitations should be acknowledged. First, the analysis is based on provincial-level data, which may obscure disparities within provinces at the district or household level. Second, the model relies on a fixed set of socioeconomic indicators and does not explicitly account for temporal dynamics or external shocks, such as economic crises or pandemics, that may influence poverty trends. Third, hyperparameter selection was performed using a trial-and-error approach rather than more systematic optimization methods, such as grid search or Bayesian optimization. Future research may address these limitations by employing finer-grained datasets, integrating time-series or deep learning frameworks, and applying advanced hyperparameter tuning techniques to further enhance predictive accuracy and model generalizability..

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