COMPARISON OF PERFORMANCE OF DEEP LEARNING AND RANDOM FOREST ALGORITHMS IN CLASSIFICATION OF STUNTING CASES IN TULUNGAGUNG REGION

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Abstract: Stunting is a significant public health problem, especially in Tulungagung. This phenomenon reflects nutritional imbalances and environmental conditions that affect children's growth. In order to improve understanding of the factors that contribute to stunting, this research focuses on comparing the performance of two main algorithms, namely Deep Learning and Random Forest, in the classification of stunting cases in the region. The evaluation is based on several metrics such as Relative Error, Standard Deviation, Gains, Total Time, Training Time (1,000 Rows), and Scoring Time (1,000 Rows). The results show that the Deep Learning model has a Relative Error of 0.3 with a Standard Deviation of 0.0, while the Random Forest model has a Relative Error of 0.4 with a Standard Deviation of 0.0. The Gains obtained by the Deep Learning model reached 1454.0, while the Random Forest model reached 622.0. The total time required by the Deep Learning model is 786.0, with Training Time (1,000 Rows) of 55.6 and Scoring Time (1,000 Rows) of 361.1. In contrast, the Random Forest model has a Total Time of 55.4, Training Time (1,000 Rows) of 361.1, and Scoring Time (1,000 Rows) of 55.4. This research provides an in-depth understanding of the performance comparison between Deep Learning and Random Forest algorithms in classifying stunting cases in the Tulungagung area, with consideration of time efficiency and prediction accuracy as determining factors for the success of model implementation.

INTRODUCTION

Child growth and development is an important indicator of public health, and stunting is a serious problem that affects the quality of life of young people, especially in Tulungagung (Rahutomo et al., 2022). In this context, this research aims to evaluate and compare the performance of two main algorithms, namely Deep Learning and Random Forest, in the classification of stunting cases in the region (Ananta et al., 2023; Skaramagkas et al., 2023). The main focus of the research is on understanding the factors that contribute to stunting and developing predictive models that can support the identification of such cases (Banerjee et al., 2018; Rahutomo et al., 2023).

Performance evaluation was conducted using a number of critical metrics, such as Relative Error, Standard Deviation, Gains, Total Time, Training Time (1,000 Rows), and Scoring Time (1,000 Rows) (Ali et al., 2023; Roy et al., 2020). The results revealed a comparison between Deep Learning and Random Forest models in these aspects. The Deep Learning model shows a Relative Error of 0.3 with a Standard Deviation of 0.0, while the Random Forest model has a Relative Error of 0.4 with a Standard Deviation of 0.0. The Gains obtained by the Deep Learning model reached 1454.0, while the Random Forest model reached 622.0. In addition, the total time required by each model is also an important consideration, with the Deep Learning model taking 786.0, and the Random Forest model 55.4.

This research not only provides an overview of the effectiveness of both algorithms in classifying stunting cases in the Tulungagung area but also highlights the time efficiency and prediction accuracy factors as key elements of successful model implementation in addressing complex public health issues.

RESEARCH METHODS

In the course of this comprehensive study, the research process progressed through various important stages (Dutta et al., 2020; Mishra & Mantri, 2023). The research began with meticulous data collection, to gain valuable insights into the various factors that influence the classification of stunting cases in the Tulungagung region. Next, the emphasis turned to data processing, where special attention was paid to the important task of data normalization. This process forms the basis for the subsequent implementation of the chosen algorithm, as its efficacy depends on the quality and uniformity of the processed data. To provide a visual representation of the complex research methodology, Figure 1 illustrates a flow chart through the collection, processing, and implementation of the algorithms. This graphical depiction serves as a valuable guide, explaining the systematic approach adopted in this research. After the implementation stage, the research culminates in the final stage careful assessment of the model's performance against the data set. This assessment is not only based on traditional measures of accuracy and precision, but also includes a nuanced evaluation that includes Relative Error, Standard Deviation, and Gain. This holistic approach aims to provide a comprehensive understanding of the model's efficacy in the context of classifying stunting cases in the Tulungagung region.

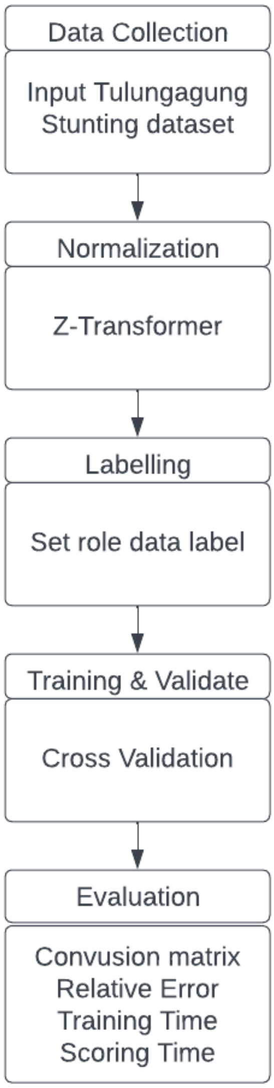

Figure 1. Flow of Data Processing

A. Variable and Sample Identification

The first step in this research was to identify the key variables required for the classification of stunting cases in Tulungagung. This involved an in-depth understanding of factors such as nutritional, environmental, and child health conditions. In addition, a representative sample of the population in the area was selected, with the aim of maximizing the generalizability of the results.

B. Data Collection and Preprocessing

The next process is data collection, which is done through field surveys and secondary data mining from relevant institutions. The next step included data cleaning to deal with missing values, extreme data, and variable transformation where necessary. The importance of data normalization was also emphasized to ensure the consistency and accuracy of the model during the analysis. data was obtained from the open data of the Tulungagung district government and can be downloaded by everyone.

- Relative Error or relative error shows the magnitude of the difference in the predicted value of the model against the actual data divided by the actual value. The smaller the relative error the more accurate the prediction model (Sotnikov et al., 2023).

$$Relative\ Error = |Actual\ Value - Predicted\ Value| \ /\ Actual\ Value \qquad (1)$$

- Standard Deviation Standard deviation is an important statistical measure of dispersion, indicating the variability of the data distribution concerning the population mean (Reddy & Parvathy, 2022).

$$SD = \sqrt{}\ \Sigma(xi - \mu)2 \ /\ (n-1) \qquad (2)$$

- Gains Gains measure the accuracy of the model in predicting positive targets after taking into account the false alarm rate (Shen et al., 2023).

$$Gains = Hit\ Rate - False\ Alarm\ Rate \qquad (3)$$

C. Feature Selection and Dimension Reduction

Statistical analysis is used to select the features that are most relevant to the stunting classification objective. This feature selection focuses on variables that have a significant impact on the final result. Next, dimensionality reduction was performed to improve the efficiency of the algorithm and speed up the analysis process.

D. Use of Machine Learning Algorithms

After data processing, the next step in the research methodology involves applying the selected machine learning algorithm (Hussein et al., 2019). As this stage progresses, the algorithm parameters are carefully adjusted to ensure that the resulting model has the optimal ability to classify stunting cases. This process involves setting key variables and other adjustments so that the algorithm can capture significant patterns and relationships in the data.

To provide a clearer visual representation of this process, Figure 1 visualizes these steps sequentially. It also provides insight into the complexity and interconnectedness of the research stages, from data collection to algorithm implementation. By understanding the sequence and relationship between the steps, this research is expected to contribute to a deeper understanding of the factors that influence stunting cases in Tulungagung.

In line with the algorithm implementation, this research focuses on evaluating the model performance by considering critical metrics, including Relative Error, Standard Deviation, and Gains. This holistic evaluation approach is designed to provide a thorough understanding of the extent to which the model is able to classify stunting cases accurately and is responsive to complex data variance. By incorporating these metrics, this research utilizes a more comprehensive and in-depth approach in evaluating and understanding the predictive quality of the model.

Table 1. Confusion matrix

	Classification Results										
	K1	**K2**	**K3**	**K4**	**K5**	**K6**	**K7**	**K8**	**K9**	**…**	**K20**
K1	X										
K2		X									
K3			X								
K4				X							
K5					X						
K6						X					
K7							X				
K8								X			
K9									X		
…										X	
K20											X

E. Model Validation and Results Analysis

The generated model was then validated using cross-validation techniques to measure its performance. The data was divided into training and testing subsets, allowing evaluation of the generalizability of the model. Analysis of the results is done by detailing critical metrics such as Relative Error, Standard Deviation, Gains, and computation time. Interpretation of the results provides an in-depth understanding of the performance comparison between Deep Learning and Random Forest algorithms in the context of stunting case classification in Tulungagung region.

RESULTS AND DISCUSSION

A. Relative Error, Standard Deviation, and Gains

In evaluating model performance, several important metrics are measured, including Relative Error, Standard Deviation, and Gains. The results show that the

Deep Learning model has a Relative Error of 0.3 with a Standard Deviation of 0.0, while the Random Forest model has a Relative Error of 0.4 with a Standard Deviation of 0.0. This difference indicates that the Deep Learning model tends to provide predictions that are closer to the true value than the Random Forest model.

Gains, which measures the improvement in prediction from the model against the baseline, reached 1454.0 for Deep Learning and 622.0 for Random Forest. This indicates that the Deep Learning model provides a more significant improvement in prediction compared to the Random Forest model.

- Deep Learning

Table 2. Weight Deep Learning

Attribute	**Weight**
Prevalensi	0,9
KECAMATAN	0,0
Puskesmas	0,0

In the Deep Learning model used, there are certain attributes that have weight values that determine how much they contribute to the learning and decision-making process. For example, the Prevalence attribute has a weight of 0.9, indicating that information related to prevalence has a significant influence in forming model predictions. On the other hand, the KECAMATAN and Puskesmas attributes have a weight of 0.0, indicating that in the context of this model, both attributes do not contribute or are not used in the learning process. The weights of these attributes reflect the extent to which they influence the prediction results, with a high value signifying a large influence and a low or zero value signifying a minimal or irrelevant contribution to the model learning.

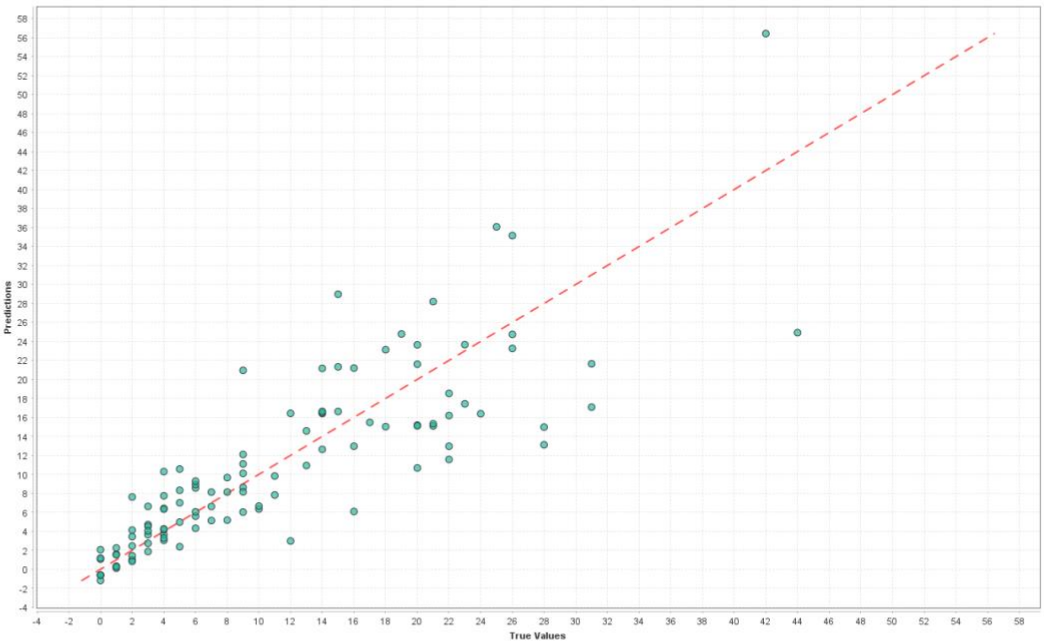

Figure 2. Prediction Chart

In the Tulungagung area, stunting cases are a serious concern, and this study attempts to simulate predictions related to these cases. Figure 2 provides a visualization of the prediction results with dots reflecting the truth value, i.e., predictions that match the original data. The red line marks the boundary between the actual data and the prediction results, providing very important information. Stunting, a condition in which a child's growth is unbalanced in terms of both height and brain development, is often caused by malnutrition over a long period of time. Stunting can be triggered by various factors, including malnutrition, anemia, or other nutritional problems. Therefore, monitoring and predicting stunting conditions is crucial to identify problems and maintain children's health. The prediction method used in this study involves analyzing clinical data, such as height, weight, and health conditions, as well as demographic data such as age, gender, and social status. The prediction results generated by the model can provide significant support in identifying stunting cases early, allowing monitors to make better decisions regarding child health management. In this context, the use of Figure 2 with red dots and lines is key in providing a clear visualization of the relationship between the original and predicted data. This helps monitors to better understand the progression of stunting cases and provides a solid basis for better decision-making in child health management.

- Random Forest

Table 3. Weight Random Forest

Attribute	**Weight**
Prevalence	0,7
KECAMATAN	0,1
Puskesmas	0,0

In the Random Forest model, certain attributes also have weights that influence the learning and decision-making process. For example, the Prevalence attribute has a weight of 0.7, indicating a significant contribution in the formation of decisions by the model. Information related to prevalence has a considerable influence on the model's predictions. The KECAMATAN attribute, with a weight of 0.1, contributes less than Prevalence but still has an influence in the learning process of the Random Forest model. In contrast, the Puskesmas attribute has a weight of 0.0, indicating that this attribute does not make a significant contribution or may not even be used in the formation of predictions by the model. The attribute weights in the Random Forest model reflect the level of importance of each attribute in collective decision making by the set of decision trees that make up this model. A high weight value indicates a greater contribution, while a low or zero weight value indicates minimal or irrelevant contribution.

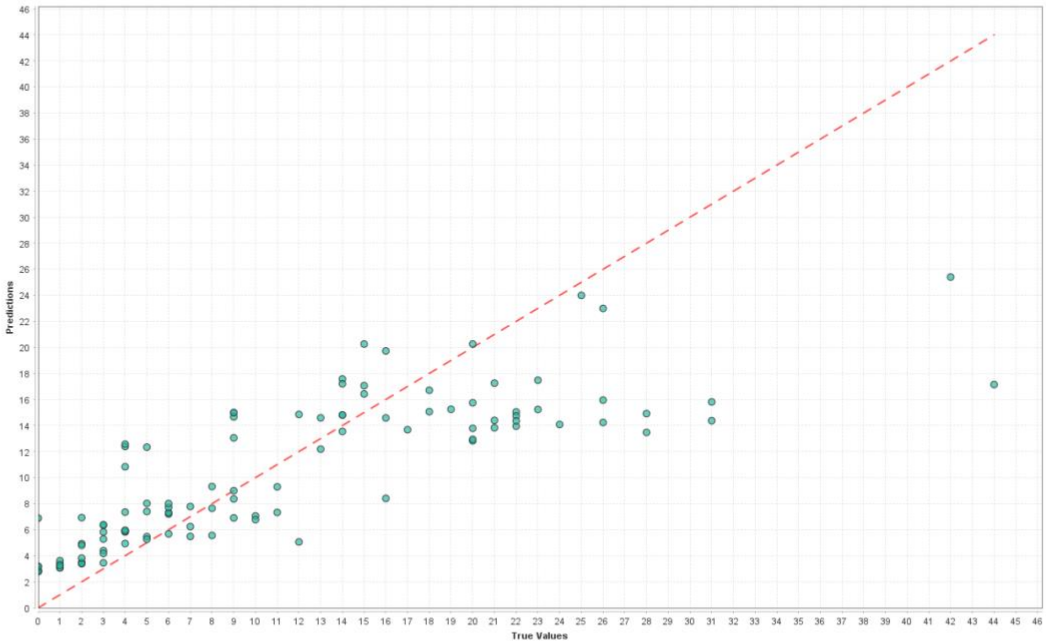

Figure 3. Prediction Chart

Table 4. Comparison of Deep Learning and Random Forest

Model	Relative Error	Standard Deviation	Gains	Total Time	Training Time (1,000 Rows)	Scoring Time (1,000 Rows)
Deep Learning	0,3	0,0	5.621 +/- 1.266	1454,0	786,0	55,6
Random Forest	0,4	0,0	6.043 +/- 1.876	622,0	55,4	361,1

Table 4 presents the performance evaluation results of two machine learning models, Deep Learning and Random Forest, in the case of stunting classification in Tulungagung. For both models, the Relative Error metric indicates the extent of the difference between predicted and actual values, with Deep Learning having a value of 0.3 and Random Forest at 0.4. Standard Deviation, indicating the variability of the prediction results, has a value of 0.0 for both models, indicating consistency of predictions. Gains, which reflect the improvement in prediction from the baseline, showed that the Deep Learning model had a Gains of 1454.0, while Random Forest had a value of 622.0. The total time required for training and testing is faster for the Random Forest model (55.4) compared to Deep Learning (786.0). Training Time (1,000 Rows) shows the training time on 1,000 rows of data, with Deep Learning taking 55.6 and Random Forest 361.1. Scoring Time (1,000 Rows) shows the testing time on 1,000 rows of data, with Deep Learning taking 361.1 and Random Forest 55.4. Analysis of these results provides a comprehensive overview of the relative performance of the two models, providing considerations on prediction accuracy, stability, improvement from baseline, and time efficiency. This evaluation serves as an important basis for selecting the model that best suits the needs and practical goals of implementation in the field, particularly in relation to reducing stunting cases in Tulungagung.

a. Total Time and Training Time

In terms of time efficiency, the Deep Learning model requires a total time of 786.0, with a Training Time (1,000 Rows) of 55.6. On the other hand, the Random Forest model has a Total Time of 55.4, with a Training Time (1,000 Rows) of 361.1. Although the Random Forest model requires less time for training, this comparison must be balanced with the predictive performance of each model.

b. Discussion

These results show that while the Random Forest model requires shorter training time, the Deep Learning model provides more accurate predictions with lower Relative Error and higher Gains. Nonetheless, the trade-off between training time and predictive performance should be carefully considered in practical implementation, depending on the specific needs and constraints of the application in the field. The decision to choose an appropriate model should take these factors into account and can be customized based on the desired applicative goals. This discussion opens up space for further understanding of how model selection can affect practical outcomes and implementation sustainability in the context of stunting prevention in Tulungagung.

CONCLUSIONS AND RECOMMENDATIONS

Based on the performance evaluation results, it was found that the Deep Learning model showed higher prediction accuracy, while the Random Forest model was more time efficient in Total Time and Training Time (1,000 Rows). Therefore, in choosing between these two models, the decision should be based on specific needs and the balance between accuracy and time efficiency. Although the Deep Learning model showed lower Relative Error (0.3) compared to Random Forest (0.4), and much higher Gains (1454.0), time efficiency is an important consideration. The Random Forest model takes less time in Total Time (55.4) and Training Time (1,000 Rows) (55.4) compared to the Deep Learning model (786.0 and 55.6). However, the time efficiency of the Random Forest model is offset by lower prediction accuracy and improvement.

Recommendations were made to further fine-tune both models, consider integrating additional information such as socio-economic or environmental data, and involve external validation with independent datasets to test the generalizability of the model beyond the training dataset. Close collaboration with stakeholders, including health institutions and local government, is also proposed to ensure more effective and relevant implementation of the models in addressing stunting cases in Tulungagung.

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