Optimizing Deep Learning with Integrated Data Balancing Strategies for Multiclass Stunting Prediction

Manuscript received May 21, 2025; revised July 18, 2026

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***Abstract*— Accurate prediction of stunting among toddlers plays a vital role in enabling early intervention and supporting data-driven public health planning. Nonetheless, constructing robust predictive models remains a challenge due to significant class imbalance and heterogeneous data characteristics derived from multiple sources. This research proposes an enhanced Deep Neural Network (DNN) model for multiclass stunting classification by integrating advanced data balancing (SMOTE, SMOTE-NC, and SMOTE-ENN). The model was trained using anthropometric data obtained from both primary and secondary datasets. Experimental evaluations indicate that the combination of the DNN and SMOTE-ENN model yielded optimal performance, obtaining an accuracy of 98.57%, precision of 98.59%, F1-Score of 98.58%, and ROC-AUC of 99.97%. The confusion matrix analysis showed a similar misclassification pattern, predominantly between the Severely Stunted and Stunted classes and between the Normal class and the adjacent growth-status classes, which suggests a considerable overlap of features between adjacent classes. Furthermore, the smooth training and validation loss curves show that the proposed model can effectively avoid the underfitting and overfitting problems, guaranteeing the reliability and robustness of the prediction. Overall, the combination of DNN+SMOTE-ENN was the best approach to deal with class imbalance, enhance class separation, and boost the performance of multiclass stunting classification.**

Keywords*— *Deep Neural Networks, Imbalanced Data Handling, Multiclass Classification, SMOTE-ENN, Stunting Classification.

I. INTRODUCTION

Stunting refers to a growth disorder caused by prolonged nutritional deficiency, leading to hindered physical and developmental progress in children. It contributes to various negative impacts on both physical and cognitive health. Children experiencing stunting tend to have delayed cognitive development, difficulties in education, reduced productivity, and an increased risk of recurrent chronic diseases [1], [2], [3]. This condition primarily impacts children below five years of age, with nearly 70% of stunting cases found among those aged 0 to 23 months [4]. Stunting is attributed to multiple factors, including inadequate nutrition, limited maternal knowledge, poor sanitation and hygiene, and other contributing factors [5]. According to the 2022 WHO report, an estimated 148.1 million children under five worldwide suffer from stunting, making it one of the most significant global health challenges.

To assess this condition, anthropometric status evaluation is conducted by calculating the Z-score, following the standards set by the Indonesian Ministry of Health. The threshold used is a Z-score between <-2 and <-3 standard deviations, indicating the severity level of stunting in children [6], [7]. Many studies, both in medical settings and other areas, have looked into the best ways to use supplements to help children who are stunted. These supplements include vitamins and other essential nutrients, and they are given directly to toddlers through pills, liquid drops, or specially made foods that have extra nutrients added [8], [9]. On the other hand, advancements in artificial intelligence (AI) have opened new opportunities for stunting prevention and early detection through data-driven approaches. Deep learning methods have been applied in artificial intelligence to improve the capability of automatic detection [10]. Owing to their strength in handling large-scale and complex datasets, both deep learning and machine learning algorithms can be employed to build systems that efficiently and autonomously identify stunting cases [11].

Many previous studies have looked into how to classify and predict stunting. Chilyabanyama et al. [12] did a study to identify stunting using several machine learning methods, and their findings showed that the random forest method worked best, with an accuracy of 79%. Similarly, Syahrial et al. [13] and Andriyani et al. [14] employed an SVM model with a Radial Basis Function for the classification of stunting and achieved an accuracy rate of 78%. In another study, Amin et al. [15] applied anthropometric measurements and an LSTM network to predict stunting, attaining an accuracy of 81.53%. Meanwhile, Lestari et al. [16] implemented a Deep Neural Network (DNN) model for stunting classification in early childhood, achieving an accuracy rate of 83.85%. Ananta et al. [17] employed a location-based approach and SVM to classify stunting cases in East Java, achieving 87% accuracy. Even though many machine learning methods have been studied for predicting stunting, the accuracy of the models that are currently available is still not good enough. This limitation is primarily due to the small dataset size and the imbalance in class distribution, which prevents models from effectively

 EISSN: 2961-872X ●PISSN: 2961-8924●DOI: 10.56741/IISTR.esl.002311

recognizing patterns across different stunting categories. Therefore, effective data-balancing strategies are required to enhance model performance and improve prediction accuracy.

Several studies have explored methods to improve stunting prediction accuracy, including oversampling techniques to balance data. The Synthetic Minority Oversampling Technique (SMOTE) has been extensively utilized to overcome the issue of class imbalance because it generates new synthetic examples within the minority class [18]. Sutoyo et al. [19] successfully applied SMOTE to handle data imbalance in television advertisement performance classification. Additionally, various studies have demonstrated the effectiveness of SMOTE with different machine learning models, such as SMOTE + XGBoost with 85.74% accuracy [20], SMOTE + Random Forest with 88.90% accuracy [21], SMOTE + ANN with 90% accuracy [22], and SMOTE + SVM with 90.5% accuracy [23]. However, these studies primarily focused on binary classification, leaving gaps in the development of models for multiclass classification. This study is conducted to address existing limitations by developing a deep learning-based multiclass stunting classification framework optimized through advanced data balancing methods. Multiclass classification for stunting is crucial as it enables the identification of different severity levels, allowing for more targeted intervention strategies. In this research, DNNs are utilized for multiclass classification. In recent years, DNNs have exhibited strong performance across multiple domains, notably in image recognition, language processing, and medical analysis.

Although determining which input features influence model decisions remains a challenge, DNNs remain a vital tool in machine learning. This analytical process plays a crucial role across various sectors, including legislation, law enforcement, and healthcare, to ensure that DNN-based decisions align appropriately with their application context [24]. Lestari and Ulina [25] combined DNN and data normalization to optimize web phishing predictions, achieving an accuracy of 95.01%. DNNs have also been widely applied to classification problems, including Alzheimer's disease identification [26]. Trivedi et al. [27] used DNN for disease classification in tomato leaves, achieving 98.49% accuracy. Mubarakah et al. [28] implemented DNN for image validation, obtaining 94.31% accuracy. Joloudari et al. [29] combined SMOTE and DNN to address data imbalance in classification tasks and achieved an accuracy of 98.96%.

To further optimize the performance of the DNN model in multiclass stunting classification, this study contributes to the development of an enhanced prediction model through the application of multiple oversampling strategies (SMOTE, SMOTE-NC, and SMOTE-ENN) to address class imbalance within the dataset. This process is further refined by applying StandardScaler normalization to standardize feature distributions, enabling more effective model learning. In addition, the integration of primary and secondary datasets enriches the information available to the model, thereby improving prediction accuracy. Through this comprehensive approach, the study contributes to the creation of a more accurate and reliable stunting classification model, which can serve as a valuable tool in public health policymaking for stunting prevention and early intervention efforts.

II. METHODS

This research methodology details the sequential stages of the research design process. The research framework is presented in Fig. 1.

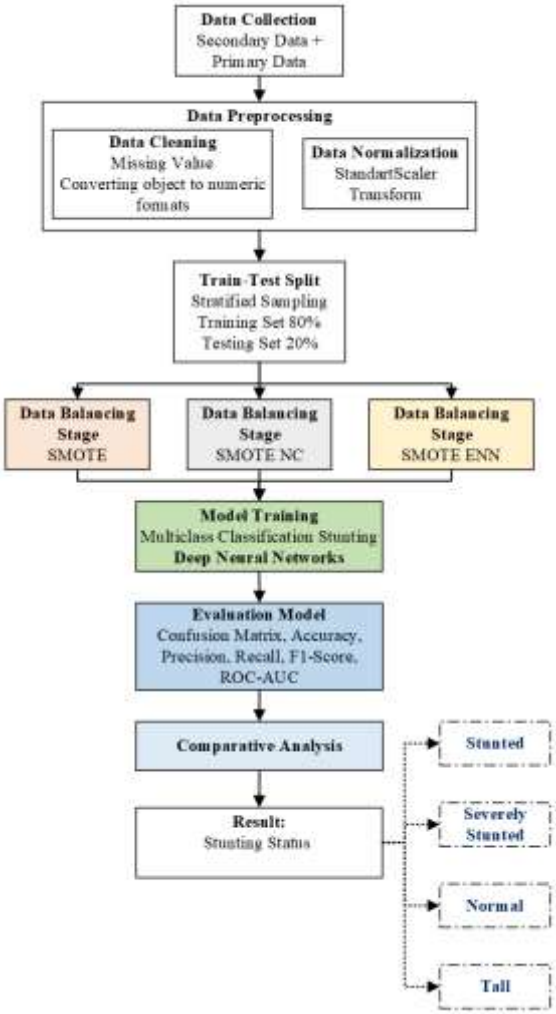


Fig 1. Research Design for Multiclass Stunting

A. Data Collection

This study integrates two data sources:

1. Primary Data: The primary dataset was gathered from a private general hospital (RSU) in Medan, Indonesia. The dataset contains 17 records of stunting data of children under five collected throughout 2023. Incorporating primary data ensures the study reflects recent and localized cases, thereby increasing the relevance and practical applicability of the findings.
2. Secondary Data: The secondary dataset, obtained from Kaggle, comprises 121,000 records of stunting cases in children under five [30]. This publicly accessible dataset serves as a large-scale reference to improve model training and validation.

By combining these two datasets, the study leverages both large-scale publicly available data and real-world hospital records, improving the model's generalizability and accuracy in predicting stunting.

B. Data Preprocessing

Data preprocessing is a process used to enhance the quality of data and ensure compatibility with machine learning algorithms. This process consists of three main steps:

1. Data Cleaning: Data cleaning is performed to ensure that the data is free of inconsistencies that could negatively

impact model performance. This process includes handling missing values and data type conversion. Missing data can negatively affect model performance and introduce bias in predictions; therefore, a comprehensive analysis is performed to identify and handle missing values. In addition, categorical variables stored as object-type data are converted to numerical representations to facilitate computational processing. In this research, the label encoding technique is used to transform categorical variables, ensuring that the data is properly formatted prior to the model training phase.

2. Data Normalization: To standardize feature scales and improve model convergence, the StandardScaler Transformation is applied. This normalization step is essential for optimizing gradient-based learning algorithms and improving model stability.

C. *Train-Test Split*

The pre-processed dataset was divided into training and testing subsets using a stratified sampling strategy with a ratio of 80:20. For both subsets, stratified sampling was used to preserve the original class distribution and to obtain a fairer evaluation of the classification models while reducing sampling bias.

D. *Data Balancing Stage*

This study employs a specific strategy for training data balancing to address class imbalance and enhance a model's performance for all data types. The imbalance in the class leads to biased predictions in which the model prefers the majority class and under-represents the minority class. To solve this problem, three variations of SMOTE are utilized, namely SMOTE, SMOTE-NC (SMOTE for Nominal and Continuous Data), and SMOTE-ENN (SMOTE with Edited Nearest Neighbors). SMOTE generates a more balanced dataset without sample replication and so enables the model to better understand the class distribution. SMOTE-NC is an extension of SMOTE for datasets comprising both categorical and numerical variables. SMOTE-NC uses particular procedures to create synthetic examples while retaining the integrity of categorical attributes, which cannot be interpolated directly. This ensures that mixed-type data is handled correctly. SMOTE-ENN combines oversampling and under-sampling to increase the quality of data. After generating synthetic samples, the Edited Nearest Neighbors (ENN) method removes noisy and ambiguous examples, particularly from the majority class. This hybrid approach helps to avoid overfitting and to keep the dataset balanced. Thus, these strategies are incorporated to balance the training data effectively to increase the classification accuracy and reduce bias, and to make sure the predictive models work consistently in all categories for real-world applications. For all balancing procedures, only the training dataset was used to avoid data leakage and enable an unbiased evaluation of the trained models. The testing dataset was never subjected to any oversampling or data augmentation process and was used exclusively for model evaluation.

E. *Model Training*

A DNN model was constructed to perform multiclass stunting prediction. The architecture was structured with multiple hidden layers to capture and learn intricate patterns embedded within the dataset. As illustrated in Fig. 2, the DNN model comprises several key components:

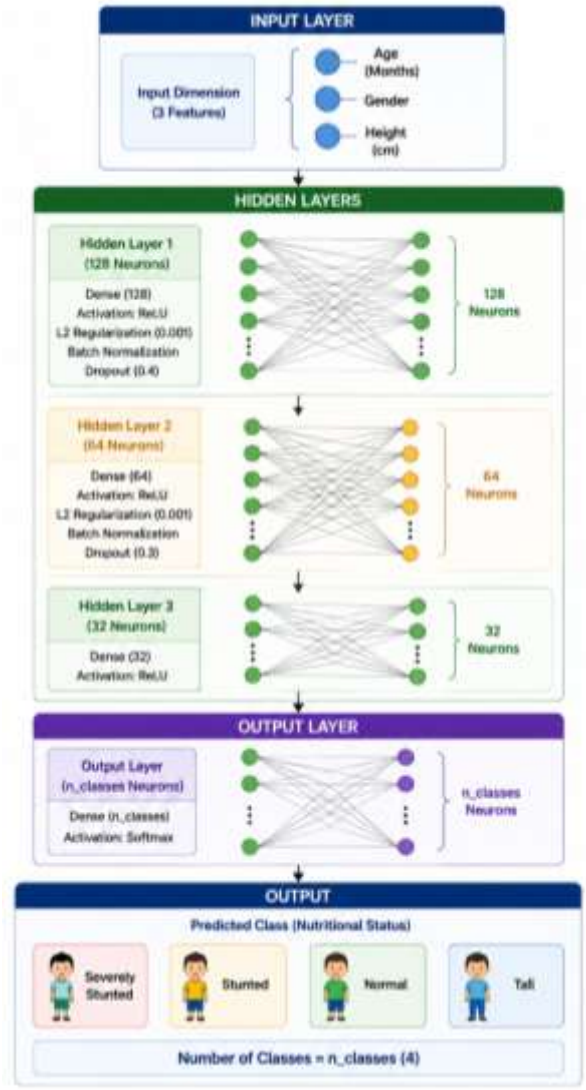


Fig. 2. Deep Neural Networks Architecture

1. Input Layer: Accepts numerical features that have undergone preprocessing.
2. Hidden Layers: Consists of multiple hidden layers equipped with ReLU activation functions to capture data nonlinearity effectively.
3. Output Layer: The output layer uses the Softmax function to create probability distributions for each class in the multiclass classification task.

Table I shows the DNN parameter configuration, which is designed to optimize the model's generalization ability while mitigating the risks of overfitting and underfitting.

F. *Evaluation Model*

To check how well the proposed model works in predicting different types of stunting, this study uses several evaluation methods (accuracy, confusion matrix, precision, recall, F1-Score) to fully understand the model's ability to make predictions. The confusion matrix is a key tool that compares what the model actually predicted with the real outcomes, helping to see how well it performs in each category. By looking at this matrix, we can find out how many cases were correctly predicted, which shows how accurate the model is and how well it works with the whole dataset. Also, the confusion matrix helps find out where the model made

 EISSN: 2961-872X ●PISSN: 2961-8924●DOI: 10.56741/IISTR.esl.002311

mistakes and is used to calculate important performance measures.

TABLE I. CONFIGURATION OF DNN PARAMETERS

Parameters	Configuration
Input Layer	3 features
Hidden Layers	3 hidden layers
Number of Neurons	128, 64, and 32 neurons
Activation Function	Input & Hidden Layer: ReLU Output Layer: Softmax with 4 neurons
Regularization Method	L2 Regularization (0.001), Dropout (0.4 and 0.3), Batch Normalization
Optimization Function	Adam
Learning Rate	0.0001
Loss Function	Categorical Crossentropy
Batch-Size	32
Epochs	50 iterations

In addition, the study uses the ROC-AUC to see how well the model can tell apart different classes. For multi-class problems, the one-vs-rest (OvR) method is used, where each class is checked against all the other classes. A higher ROC-AUC score indicates stronger discriminative capability, ensuring that the model effectively distinguishes between stunting categories.

G. Comparative Analysis

Finally, the performance of the three proposed models (SMOTE + DNN, SMOTE-NC + DNN, and SMOTE-ENN + DNN) was evaluated based on the evaluation metrics acquired from the testing dataset. Comparative research was performed to discover the optimal data balancing technique for multiclass stunting classification in terms of predictive performance, robustness, and generalization power.

III. RESULTS AND DISCUSSION

This section describes the results of using the proposed model and includes a thorough look at the research outcomes. The study began with preparing the data to make sure it was accurate and ready for training the model. The process involved handling missing data and changing categories into numbers so that machine learning models could work with them better. The analysis showed there were no missing values, so we didn't need to use any methods to fill them in. Also, categorical data like gender and status were converted into numbers to help the model work better while keeping the original data's meaning. One big challenge in classifying stunting is that some categories have very few examples compared to others, which is called class imbalance. To fix this, we used data balancing methods such as SMOTE, SMOTE-NC, and SMOTE-ENN. After that, we normalized the features using StandardScaler to make sure all variables were on the same scale. This step is important because it helps the model train more effectively, especially for DNNs, which are sensitive to differences in data scales.

The DNN model was developed to categorize stunting into four distinct groups: normal, tall, stunted, and severely stunted. The model's configuration is depicted in Table I to enhance the model's efficacy on novel data and prevent overfitting. The Adam optimizer was employed to modify the model parameters, with a learning rate set to 0.0001. Categorical cross-entropy was the loss function employed for the multiclass classification. The model underwent training in batches of 32 for a total of 50 epochs, with the objective of attaining optimal performance. The findings indicated that the proposed DNN model exhibited high accuracy, thereby substantiating its efficacy in differentiating between various stunting categories, as shown in Table II.

The performance comparison of the Deep Neural Networks (DNN) model with three distinct data balancing strategies, SMOTE, SMOTE-NC, and SMOTE-ENN, is shown in Table II.

TABLE II. EXPERIMENTAL RESULTS OF DNN MODEL WITH DATA BALANCING TECHNIQUE

Matrix (%)	DNN + SMOTE	DNN + SMOTE-NC	DNN+ SMOTE-ENN
Accuracy	97.65	97.59	98.57
Precision	97.70	97.78	98.59
Recall	97.65	97.59	98.57
F1-Score	97.66	97.63	98.58
ROC-AUC	99.93	99.94	99.97

In general, all three models performed a good classification, with accuracy values above 97% and ROC-AUC values above 99%, showing that the proposed DNN architecture is highly successful for multiclass stunting classification. The best overall performance of all the methods tested was achieved by DNN with SMOTE-ENN. It got the best Accuracy (98.57%), Precision (98.59%), Recall (98.57%), F1-Score (98.58%), and ROC-AUC (99.97%). These results imply that the hybrid oversampling and data-cleaning approach employed by SMOTE-ENN might provide a more representative training dataset while reducing noisy and confusing samples. Consequently, the DNN model was able to learn more discriminative decision boundaries, leading to improved classification performance across all nutritional status categories.

The DNN + SMOTE model likewise performed competitively with an Accuracy of 97.65%, Precision of 97.70%, Recall of 97.65%, F1-Score of 97.66%, and ROC-AUC of 99.93%. The class imbalance problem was solved by applying SMOTE, which created new samples of the minority class, resulting in a considerable improvement in the model's generalization. SMOTE did not delete noisy observations and simply oversampled. However, its performance was still slightly lower than SMOTE-ENN. Similarly, the DNN + SMOTE-NC model has shown promising classification results with Accuracy 97.59%, Precision 97.78%, Recall 97.59%, F1-Score 97.63%, and ROC-AUC 99.94%. SMOTE-NC is particularly developed to work on datasets that contain both numerical and categorical variables, therefore potentially acceptable for stunting datasets. Nevertheless, the experimental results indicate that its performance was marginally lower than SMOTE-ENN, suggesting that preserving categorical information alone was insufficient to outperform the additional noise reduction provided by the Edited Nearest Neighbors (ENN) algorithm.

Overall, the findings demonstrate that SMOTE-ENN is the most effective data balancing technique among the three evaluated approaches. Compared with conventional SMOTE and SMOTE-NC, the integration of ENN after synthetic oversampling enables the removal of noisy and overlapping samples, thereby producing a cleaner training dataset and enhancing the learning capability of the DNN model. This improvement is consistently reflected across all evaluation metrics, confirming that DNN + SMOTE-ENN provides the most robust and reliable solution for multiclass stunting classification.

In addition to measuring accuracy, the model was also evaluated by analyzing the loss value to ensure model stability and performance. The loss value reflects how well the model

predicts the data by comparing its output to the actual values. In this study, loss analysis was used to identify potential underfitting or overfitting. Fig. 3, Fig. 4, and Fig. 5 present the loss values obtained for the three models.

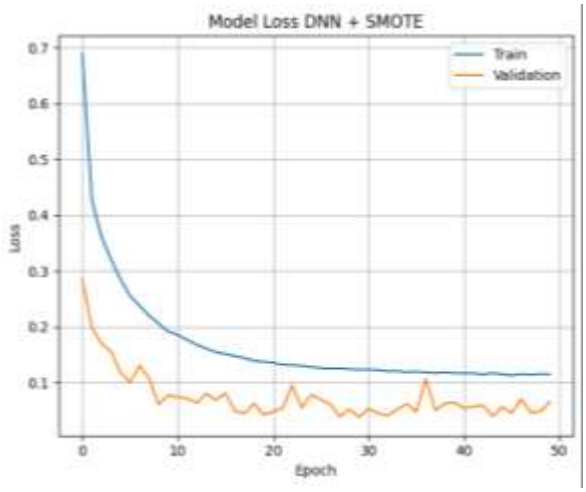


Fig. 3. Loss Value DNN + SMOTE Model

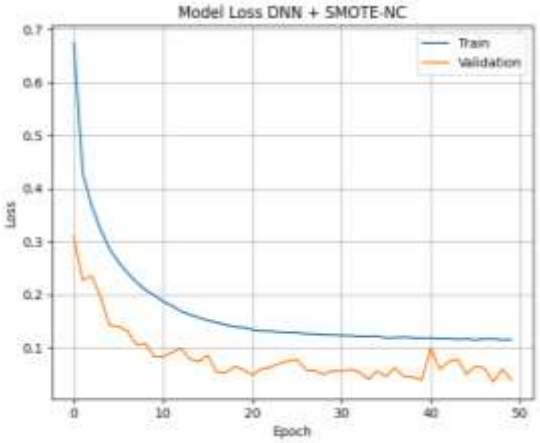


Fig. 4. Loss Value DNN + SMOTE-NC Model

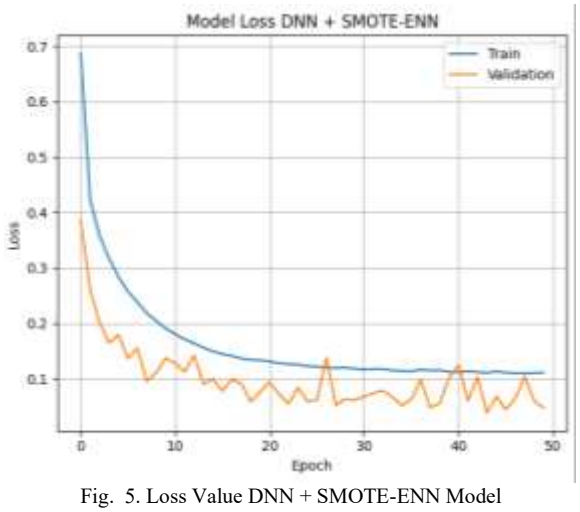


Fig. 5. Loss Value DNN + SMOTE-ENN Model

As shown in Fig. 3, Fig. 4, and Fig. 5, all proposed models converged to low loss values, reflecting stable optimization during training and good generalization performance. The DNN+SMOTE-ENN model achieved the lowest final loss (0.1110), outperforming DNN+SMOTE (0.1153) and DNN+SMOTE-NC (0.1154). Although the differences are relatively small, the lower loss obtained by DNN+SMOTE-ENN indicates a more effective learning process, which is consistent with its superior classification performance reported in Table II.

The convergence gap between training and validation losses remained small across all models, indicating stable generalization performance and minimal overfitting or underfitting. To further evaluate the classification performance of each method, the confusion matrix results for the DNN model with different data balancing techniques are shown in Fig. 6, Fig. 7, and Fig. 8.

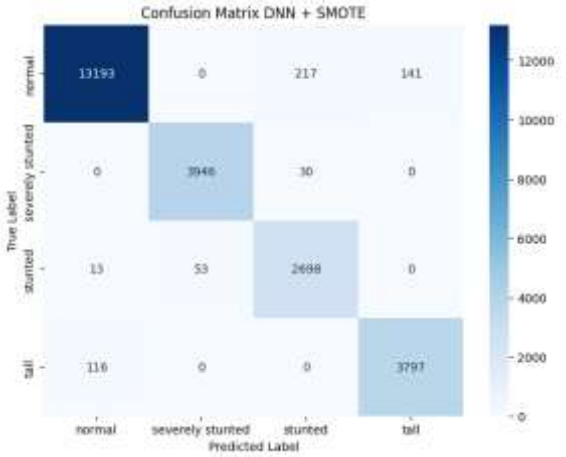


Fig. 6. Confusion Matrix DNN + SMOTE Model

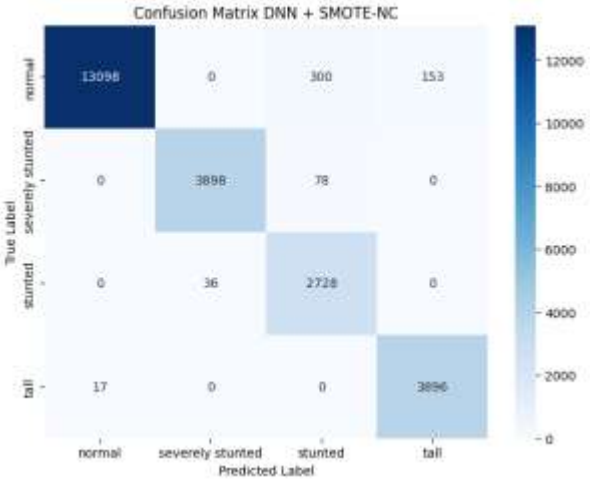


Fig. 7. Confusion Matrix DNN + SMOTE-NC Model

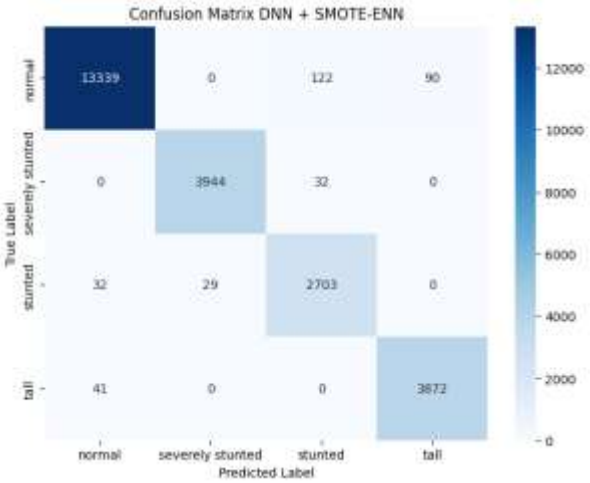


Fig. 8. Confusion Matrix DNN + SMOTE-ENN Model

 EISSN: 2961-872X ●PISSN: 2961-8924●DOI: 10.56741/IISTR.esl.002311

From the confusion matrix results of the three data balancing strategies (SMOTE, SMOTE-NC, and SMOTE-ENN), several important findings can be systematically highlighted.

1. All three balancing techniques consistently produced high classification performance, as indicated by the dominance of correctly classified instances (true positives) along the diagonal of each confusion matrix. This demonstrates that the DNN model is capable of learning discriminative patterns across all four classes (Normal, Severely Stunted, Stunted, and Tall), even under initially imbalanced conditions.
2. A more detailed analysis shows that the classification performance depended on the class and the balancing method. The Severely Stunted and Stunted classes had the most pronounced bidirectional misclassification pattern. In the SMOTE approach, 30 instances of Severely Stunted were misclassified as Stunted and 53 Stunted instances were predicted as Severely Stunted. The same trend was observed in the case of SMOTE-NC, where 78 Severely Stunted instances were misclassified as Stunted and 36 Stunted instances were classified as Severely Stunted. Conversely, SMOTE-ENN reduced these errors to 32 and 29 cases, respectively. This result shows high similarity in the anthropometric characteristics of the children of these two categories, making the decision boundary intrinsically difficult to separate. The less confusion for the SMOTE-ENN model suggests that the Edited Nearest Neighbors (ENN) cleaning mechanism is effective in removing the noisy and ambiguous samples, therefore leading to more distinct decision boundaries between the Severely Stunted and Stunted classes.
3. Across all balancing approaches, the most difficult class to classify was the Normal class. Most of the misclassification was from normal children predicted as Stunted or Tall. In particular, SMOTE produced 217 mistakes from Normal to Stunted and 141 from Normal to Tall. For SMOTE-NC, the corresponding values increased to 300 and 153 instances. In contrast, SMOTE-ENN reduced these errors significantly to 122 and 90, respectively. Thus, children who are classified as Normal may often have anthropometric measurements that are within the range of adjacent growth categories, particularly those close to clinical decision points. This issue is important from a practical point of view as misclassification of normal children as stunted may increase false positive screening outcomes and may potentially lead to unnecessary nutritional interventions.
4. The Tall category had the highest consistency of classification among all categories. Misclassification was limited to predictions into the Normal class, with almost no confusion with either Stunted or Severely Stunted. Interestingly, SMOTE-NC had the least number of misclassifications for this class, with just 17 Tall instances being wrongly predicted as Normal, as opposed to 41 with SMOTE-ENN and 116 with SMOTE. This result shows that SMOTE-NC is very effective in preserving the unique characteristics of the Tall class and making it more distinguishable from other classes.
5. The different balancing methods showed a common error structure. The Normal class was frequently mixed up with Stunted and Tall. Severely Stunted and Stunted often overlapped with each other. Conversely, confusion within the Tall class was very low and almost exclusively within the Normal category. The recurrent patterns suggest that the primary cause of classification errors stems from the inherent resemblance between adjacent growth-status categories, rather than from instability within the DNN model itself. Thus, the remaining classification problems seem to be related to the underlying data distribution and to slow transitions between nutritional status categories

For the three balancing techniques, SMOTE was a strong baseline performance but still showed considerable overlap among neighboring classes. SMOTE-NC showed the best performance in the Tall category; it also had the highest misclassifications in the Normal class and increased the confusion between Severely Stunted and Stunted. In contrast, SMOTE-ENN always achieved the lowest classification errors for the Normal class and produced the best trade-off between Severely Stunted and Stunted classes. These results suggest that the combination of oversampling and noise removal mechanisms in SMOTE-ENN can effectively increase class separability and enhance the robustness of the overall classification.

Therefore, based on the confusion matrix analysis, SMOTE-ENN can be considered the most optimal balancing strategy of the proposed DNN model since it provides the most balanced classification performance among all growth-status categories with the least critical misclassification errors related to stunting identification.

Although the proposed framework had a promising prediction performance, the model was tested only on the combined dataset used in this study and was not validated with an independent external dataset from other healthcare institutions. Thus, the proposed approach is not yet fully validated in terms of generalization to different populations, healthcare settings, and data acquisition protocols. This limitation should be taken into account when interpreting the performance reported. Furthermore, this study did not consider the interpretability of the models, although the main objective of this study was to evaluate the effectiveness of different data balancing techniques in improving multiclass stunting classification. Future studies are expected to use Explainable Artificial Intelligence (XAI) methods, such as SHAP (SHapley Additive exPlanations) and Local Interpretable Model-agnostic Explanations (LIME), to clarify the contributions of features and provide transparent explanations for model predictions. Furthermore, it is advisable to validate the proposed model with independent external datasets or cross-institutional data from multiple healthcare facilities to further assess its generalizability, robustness, and clinical applicability across various populations. These improvements are anticipated to increase model transparency, enhance confidence in real-world deployment, and allow for more accurate and reliable AI-assisted stunting assessment in practical healthcare settings.

IV. Conclusion

This research demonstrates the effectiveness of Deep Neural Networks (DNN) combined with various data balancing techniques, including SMOTE, SMOTE-NC, and SMOTE-ENN, for improving multiclass classification of stunting status. Among the evaluated methods, SMOTE-ENN achieved the best overall performance, with an accuracy of 98.57%, precision of 98.59%, F1-Score of 98.58%, and ROC-AUC of 99.97%, indicating its superior capability in improving class separability and multiclass stunting classification performance.

Analysis of the confusion matrix revealed similar misclassification patterns for all balancing strategies. In particular, the Normal class was often misclassified as Stunted or Tall, and the Severely Stunted and Stunted classes were often confused with each other in both ways. The results show

that the main challenge in the classification task is still the overlapping feature distributions among neighboring growth-status classes. Significant differences were observed among the balancing techniques. SMOTE-NC was better at classifying the Tall class, but it resulted in more misclassifications in the Normal class and increased confusion between Severely Stunted and Stunted. In contrast, SMOTE-ENN consistently reduced the classification errors of the Normal class and gave the best separation between the Severely Stunted and Stunted classes. Overall, SMOTE-ENN showed the best balanced and robust classification performance, suggesting its superior ability to improve class separability while maintaining high classification accuracy.

Moreover, the analysis of loss values shows that all models maintain stable learning behavior without indications of significant underfitting or overfitting, confirming their robustness and generalization capability. Despite these promising results, misclassification in the Normal class suggests that further improvement is still necessary. Future research should focus on enhancing feature discriminability through advanced feature engineering and the integration of additional relevant variables, such as dietary patterns, socioeconomic factors, and genetic indicators. Furthermore, validating the proposed model using independent external datasets or cross-institutional data from multiple healthcare facilities is recommended to further assess its generalizability, robustness, and clinical applicability across diverse populations. These improvements are expected to further strengthen model performance and support more accurate and reliable stunting classification in practical applications.

ACKNOWLEDGMENT

This study received financial and institutional support from the Kemdiktisaintek of the Republic of Indonesia and Universitas Mikroskil. The authors sincerely acknowledge and appreciate this assistance, which greatly contributed to the successful completion of the research.

REFERENCES

[1] J. R. Khan, J. H. Tomal, and E. Raheem, "Model and Variable Selection using Machine Learning Methods with Applications to Childhood Stunting in Bangladesh," Informatics for Health and Social Care, Vol. 46, No. 4, pp. 425-442, 2021, doi: https://doi.org/10.1080/17538157.2021.1904938.

[2] M. de Onis et al., "Prevalence thresholds for wasting, overweight and stunting in children under five years," Public Health Nutrition, vol. 22, no. 1, pp. 175–179, Jan. 2019, doi: https://doi.org/10.1017/s1368980018002434

[3] C. D. Bourke, K. D. Jones, and A. J. Prendergast, "Current Understanding of Innate Immune Cell Dysfunction in Childhood Undernutrition," Frontiers in Immunology, vol. 10, p. 1728, Jul. 2019, doi: https://doi.org/10.3389/fimmu.2019.01728.

[4] H. Pohan, M. Zarlis, E. Irawan, H. Okprana, and Y. Pranayama, "Clustering stunted toddlers in Indonesia using the K-Medoids algorithm," Public Knowledge Project PLN, Vol. 3, No. 2, pp. 97–104, 2021, doi: https://doi.org/10.53842/juki.v3i2.69.

[5] J. V. Moniaga, M. Ohyver, J. Siregar, and P. H. Yauwito, "Map-type Modelling and Analysis of Children Stunting Case Data in Indonesia with Interactive Multimedia Method," Procedia Computer Science, vol. 157, pp. 530–536, 2019, doi: https://doi.org/10.1016/j.procs.2019.09.010.

[6] S. Lonang and D. Normawati, "Classification of stunting status in toddlers using K-Nearest Neighbor with backward elimination feature selection," Journal Media Informatika Budidarma, Vol. 6, No. 1, pp. 49–49, 2022, doi: https://doi.org/10.30865/mib.v6i1.3312.

[7] M. Rosyidah, Y. L. R. Dewi, and I. Qadrijati, "Effects of Stunting on Child Development: A Meta-Analysis," Journal of Maternal Child Health, Vol. 6, No. 1, 2021, https://thejmch.com/index.php/thejmch/article/view/522.

[8] S. Zaleha and H. Idris, "Implementation of Stunting Program in Indonesia: A Narrative Review," Indonesian Journal of Health Administration, Vol. 10, No. 1, pp. 143–151, 2022, doi: https://doi.org/10.20473/jaki.v10i1.2022.143-151.

[9] B. R. Bait et al., "Scaling up child wasting prevention and treatment in the context of stunting prevention in Indonesia," https://www.ennonline.net/fex/67/en/scaling-child-wasting-prevention-and-treatment-context-stunting-prevention-indonesia (accessed: 2025)

[10] R. Resmiati and T. Arifin, "Classification of Breast Cancer Patients Using the Support Vector Machine Method with Backward Elimination," SISTEMASI, Vol. 10, No. 2, pp. 381-393, 2021, doi: https://doi.org/10.32520/stmsi.v10i2.1238.

[11] I. Ayuningtyas and E. U. Kasanah, "Application of SMOTE for analyzing COVID-19's impact on working-age population in East Kalimantan," BESTARI BPS Kalimantan Timur, Vol. 1, No. 1, 2021, https://bestari.bpskaltim.com/index.php/bestari-bpskaltim/article/view/3

[12] O. N. Chilyabanyama et al., "Performance of Machine Learning Classifiers in Classifying Stunting among Under-Five Children in Zambia," Children, Vol. 9, No. 7, 2022, doi: https://doi.org/10.3390/children9071082.

[13] R. Syahrial, R. Ilham, Z. F. Asikin, and S. Surya, "Stunting Classification in Children's Measurement Data Using Machine Learning Models," Journal La Multiapp, Vol. 3, No. 2, pp. 52–60, 2022, doi: https://doi.org/10.37899/journallamultiapp.v3i2.614.

[14] S. Y. Andriyani, M. S. Lydia, and S. Efendi, "Optimization of Support Vector Machine Algorithm Using Stunting Data Classification," Prisma Sains, Vol. 11, No. 1, pp. 164–171, 2023, doi: https://doi.org/10.33394/j-ps.v11i1.6619.

[15] F. M. Amin and D. C. R. Novitasari, "Identification of Stunting Disease using Anthropometry Data and Long Short-Term Memory (LSTM) Model," Comput. Eng. Appl. J., Vol. 11, No. 1, pp. 25–36, 2022, doi: https://doi.org/10.18495/comengapp.v11i1.395.

[16] W. S. Lestari, C. Caroline, and Y. M. Saragih, "Deep Learning Approach for Stunting Classification in Toddlers," Proc. 2nd Int. Conf. Technol. Innov. Appl. (ICTIIA), Medan, Indonesia, 2024, pp. 1–5, doi: https://doi.org/10.1109/ICTIIA61827.2024.10761797.

[17] C. J. Ananta, A. Fariza, and R. Asmara, "Stunting Program Classification in East Java, Indonesia From Internet News Using Location-Based and SVM," Proc. Int. Electron. Symp. (IES), pp. 527–532, 2023, doi: https://doi.org/10.1109/IES59143.2023.10242418.

[18] E. Sutoyo and M. A. Fadlurrahman, "Application of SMOTE to Overcome Class Imbalance in Television Advertisement Performance Rating Classification Using Artificial Neural Network," J. Edukasi Penelit. Informatika (JEPIN), Vol. 6, No. 3, pp. 379–385, 2020, doi: https://doi.org/10.26418/jp.v6i3.42896.

[19] S. Yadav, "SMOTE in Predictive Modeling: A Comprehensive Evaluation of Synthetic Oversampling for Class Imbalance," Int. J. Innov. Res. Eng. Multidiscip. Phys. Sci., Vol. 8, No. 4, 2020, doi: https://doi.org/10.5281/zenodo.14259555.

[20] T. Sugihartono, B. Wijaya, M. Marini, A. P. Alkayess, and H. A. Anugerah, "Optimizing Stunting Detection through SMOTE and Machine Learning: a Comparative Study of XGBoost, Random Forest, SVM, and k-NN," J. Appl. Data Sci., Vol. 6, No. 1, pp. 667–682, 2025, https://doi.org/10.47738/jads.v6i1.494.

[21] E. Miranda, M. Aryuni, A. Y. Zakiyyah, Y. E. Kurniawati, A. V. D. Sano, and M. Kumbangsila, "An early prediction model for toddler nutrition based on machine learning from imbalanced data," Procedia Computer Science, vol. 245, pp. 263–271, 2024, doi: https://doi.org/10.1016/j.procs.2024.10.251.

[22] W. M. Baihaqi, I. N. Laela, and D Darso, "Improving Stunting Classification Performance Using Combination SMOTE Technique and Artificial Neural Network Algorithm," JITK, Vol. 10, No. 1, pp. 160–167, 2024, doi: https://doi.org/10.33480/jitk.v10i1.4998.

[23] J. Minardi, F. Budiman, M. Z. Fanani, and N. Rijati, "Enhancing Stunting Detection Accuracy in Children Using SVM with Advanced Data Balancing Techniques," J. Inf. Syst. Eng. Manage., Vol. 10, No. 6s, pp. 501–509, 2025, doi: https://doi.org/10.52783/jisem.v10i6s.748.

[24] G. Ras, N. Xie, M. V. Gerven, and D. Doran, "Explainable Deep Learning: A Field Guide for the Uninitiated," Journal of Artificial Intelligence Research, Vol. 73, pp. 329–397, 2022, doi: https://doi.org/10.1613/jair.1.13200.

[25] W. S. Lestari and M. Ulina, "Optimizing Deep Neural Networks Using ANOVA for Phishing Detection," Teknika, Vol. 13, No. 1, pp. 71–76, 2024, 76, Feb. 2024, doi: https://doi.org/10.34148/teknika.v13i1.758.

 EISSN: 2961-872X ●PISSN: 2961-8924●DOI: 10.56741/IISTR.esl.002311

[26] S. Fouladi, A. A. Safaei, N. Mammone, F. Ghaderi, and M. J. Ebadi, "Efficient Deep Neural Networks for Classification of Alzheimer's Disease and Mild Cognitive Impairment from Scalp EEG Recordings," Cognitive Computation, Vol. 14, pp. 1247-1268, 2022, doi: https://doi.org/10.1007/s12559-022-10033-3.

[27] N. K. Trivedi et al., "Early Detection and Classification of Tomato Leaf Disease Using High-Performance Deep Neural Network," Sensors, Vol. 21, No. 23, p. 7987, 2021, doi: https://doi.org/10.3390/s21237987.

[28] N. Mubarakah, P. Sihombing, S. Efendi, and F. Fahmi, "Target Image Validation Modeling Using Deep Neural Network Algorithm," International Journal of Electrical and Computer Engineering (IJECE), Vol. 15, No. 2, pp. 2042–2054, 2025, doi: http://doi.org/10.11591/ijece.v15i2.pp2042-2054.

[29] J. H. Joloudari, A. Marefat, M. A. Nematollahi, S. S. Oyelere, and S. Hussain, "Effective Class-Imbalance Learning Based on SMOTE and Convolutional Neural Networks," Appl. Sci., Vol. 13, No. 6, 2023, doi: https://doi.org/10.3390/app13064006.

[30] R. P. Pradana, "Stunting Toddler (Balita) Detection (121K rows)," Kaggle.com, 2024. https://www.kaggle.com/datasets/rendiputra/stunting-balita-detection-121k-rows (accessed 2025).