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RESEARCH PAPER

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GiziLens Application for Toddler Nutritional Status Classification Using SMOTE-NC and Bayesian-Optimized Deep Learning

Sherlly Briliant Saputri, and Ledy Elsera Astrianty
Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Yogyakarta, Indonesia

ABSTRACT

Stunting is a chronic growth disorder in toddlers. Its detection is often hampered by limited conventional diagnostic methods which process the indicators of weight-for-age (W/A), height-for-age (H/A), and weight-for-height (W/H) in a fragmented manner, potentially limiting the understanding of multiple nutritional conditions in toddlers. To address this issue, this research aims to develop GiziLens, a web-based decision support system that integrates the TabNet deep learning architecture using three target-specific models trained separately but executed concurrently on the web application backend to simultaneously produce predictions for the three nutritional status indicators. This study contributes by applying TabNet optimization to local data to handle extreme class imbalance, while transforming it into a practical diagnostic tool. In its implementation, this research utilized 40,071 toddler anthropometric medical records (aged 0–59 months) from Jeneponto Regency for the 2021–2024 period. The class distribution imbalance in the dataset was mitigated using the Synthetic Minority Over-sampling Technique for Nominal and Continuous (SMOTE-NC) to regenerate minority samples until reaching a controlled residual ratio, followed by automatic optimal hyperparameter tuning using Bayesian Optimization through the Optuna framework. The evaluation results demonstrated that TabNet produced a tighter train-test generalization gap compared to MLP (0.32% vs 1.60% for W/A; 1.33% vs 2.06% for H/A; and -0.63% vs -3.56% for W/H). The TabNet model achieved a test accuracy of 96.46% (F1-weighted 0.96) for W/A, 95.88% (F1-weighted 0.96) for H/A, and 98.11% (F1-weighted 0.98) for W/H. The developed GiziLens prototype proved technical feasibility and promising retrospective predictive performance as an initial decision support system prior to conducting prospective clinical trials. The GiziLens prototype holds the potential to assist healthcare workers and program managers at Public Health Centers in accelerating integrated early stunting detection, despite the system was designed as an initial decision support instrument and cannot yet replace independent clinical diagnoses.

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CONTACT:

sherllybriliant@gmail.com
ledyelsera@uty.ac.id

I. INTRODUCTION

Stunting is a chronic growth disorder in toddlers caused by persistent malnutrition, characterized by a length or height falling below the standard deviation of the World Health Organization (WHO) growth curve [1],[2]. To support the target of reducing stunting prevalence by 14% in accordance with Presidential Regulation Number 72 of 2021, the health system ideally relies on quality data as a basis for strategic decision-making [3]. Within the framework of digital transformation, the utilization of Artificial Intelligence (AI) in the healthcare sector has the potential to enhance the efficiency of medical data analysis, although its implementation requires rigorous validation against risks to reliability and data privacy [4]. Through the use of artificial intelligence, various anthropometric indicators can be processed into holistic nutritional information representations in real-time. However, at the operational reality level, efforts to map toddler nutrition and health are still hindered, particularly in Jeneponto Regency, which recorded a stunting prevalence of 39.8% in 2022. This figure is the highest in South Sulawesi and among the top ten nationally due to limited trained health personnel and suboptimal intervention programs [5]. This condition is further exacerbated by the evolution of database architecture towards complex digital ecosystems triggering technical gaps [6]. In addition, conventional diagnostic methods that process weight-for-age (W/A), height-for-age (H/A),

Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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and weight-for-height (W/H) indicators separately cause computational models to fail in identifying dependencies across nutritional status labels and triggering clinical policy inefficiencies.

To overcome these diagnostic challenges, various recent studies have formulated intelligent computational models. One study pioneered the classification of stunting incidents using the Decision Tree C4.5 method based on z-score calculations, which offers the advantage of handling numerical and categorical data along with a high recall of 91.38%, but suffers from a moderate accuracy rate of 61.82%, high sensitivity to noise, and vulnerability due to a small sample size [7]. This computational approach was further developed by implementing Deep Neural Networks (DNNs) to predict stunting status in a multi-class manner, successfully achieving an accuracy of 93.83% with the advantage of noise-resistant complex pattern identification, although its limitations involve a lack of per-class evaluation metrics and high computational complexity [8]. Furthermore, a comparative analysis of Machine Learning algorithms proved that Random Forest performed highly superior and consistent, reaching an accuracy rate of 99.91% on massive-scale data, yet it carries the risk of extreme overfitting due to potential data leakage [9]. Methodological innovations have also been demonstrated through the combination of Extreme Gradient Boosting (XGBoost) with Bayesian Optimization and SMOTE, producing an accuracy of 98.2% and mitigating data imbalance, despite minor misclassifications on minority classes and longer computation times [10], while strengthening the Random Forest algorithm using Ensemble Learning pushed the accuracy to 98.25%, though its main drawback is the relatively marginal accuracy improvement compared to its increased computational complexity [11].

Although the current methodological landscape shows promising predictive accuracy achievements, the majority of previous studies still leave crucial research gaps, focusing on single predictions or evaluating models in isolation without comparing preprocessing protocols on mixed local data. Therefore, modeling approaches must rely on empirically validated architectural capabilities, wherein Multilayer Perceptron (MLP) has proven effective in capturing complex patterns as a fundamental model [12],[13], while the TabNet architecture is specifically designed to capture non-linear patterns in tabular data through a sequential attention mechanism that adaptively selects features [14],[15],[16]. Furthermore, the inherent vulnerability of local anthropometric datasets to uneven class distribution issues necessitates specialized handling [17], making the integration of Synthetic Minority Over-sampling Technique for Nominal and Continuous (SMOTE-NC) essential [18],[19], which is then refined through automated hyperparameter optimization based on Bayesian Optimization using Optuna to ensure performance stability [20].

The primary objective of this research is to evaluate the effectiveness of SMOTE-NC, empirically compare TabNet and MLP in classifying three primary nutritional indicators (W/A, H/A, and W/H) with Optuna optimization, and develop the "GiziLens" web-based Decision Support System. The novelty of this research lies in: (1) Technical Novelty, the combination of the SMOTE-NC hybrid oversampling technique with Optuna hyperparameter search to train three independent TabNet models robust against class imbalance; and (2) Implementation Novelty, the translation of the computational workflow into a web-based application prototype (GiziLens) with an integrated inference mechanism. This research successfully mitigated class imbalance without distorting original features, achieved automated parameter optimization to boost precision, provided academic proof through deep learning comparisons across target-specific indicators, and realized the GiziLens application to accelerate cross-sectoral stunting interventions.

This report is organized into five chapters. Chapter I outlines the background and research objectives. Chapter II details the methodology and system design. Chapter III presents the TabNet modeling and GiziLens implementation. Chapter IV discusses performance analysis and comparative studies. Finally, Chapter V provides conclusions and recommendations for future development. These clearly structured chapters collectively ensure a comprehensive understanding of the entire research project.

II. MATERIALS AND METHOD

A. Dataset

The research object of this study utilized secondary data consisting of toddler anthropometric medical records aged 0 to 59 months, meaning it did not involve human subjects or respondents recruited directly by the researchers. The unit of analysis in this study is each row of data representing the individual anthropometric and demographic profile of a toddler in Jeneponto Regency. The data source was obtained from the international public data repository Mendeley Data titled "Dataset Stunting and Nutritional Status of Toddler from Jeneponto Regency, South Sulawesi, Indonesia" [21], compiled by Asmaul Husna RS along with a research team from Universitas Negeri Makassar. The variable characteristics within this dataset comprise 10 main attributes, including gender, age in months, weight, height, as well as parameter values and standard Z-score values for Weight-for-Age (W/A), Height-for-Age (H/A) as the primary stunting indicator, and Weight-for-Height (W/H) measurements, utilizing continuous, discrete numeric, and categorical data types. Furthermore, formal ethical clearance is exempted because this study exclusively utilized public secondary data that has been anonymized

Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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from an open repository without any clinical intervention or direct contact with human subjects.

Overall, this aggregated dataset contains 40,071 toddler data records collected from 2021 to 2024, consisting of 3,412 records in 2021, 1,111 records in 2022, 3,808 records in 2023, and 31,740 records in 2024 in Microsoft Excel file format. This dataset has 10 main attribute variables that include gender, age in months, weight, height, as well as the parameters and standard deviation Z-score values for each anthropometric measurement such as Weight-for-Age, Height-for-Age as the primary indicator of stunting, and Weight-for-Height. The dominant data types in this dataset are continuous and discrete numerics for physical measurement values, and categoricals for demographic variables.

For the purposes of system training and testing, the entire dataset was partitioned into three main parts according to the research design, namely 60% training data, 30% testing data, and 10% validation data. This proportion division was designed to ensure that the processes of model parameter training, optimization, and final performance evaluation can run optimally, objectively, and free from bias. A visualization of the data record sample can be seen in Fig 1.

B. Data Collection

The dataset used in this study is secondary data; therefore, no direct anthropometric measurements were conducted on human subjects (toddlers) by the researchers, but rather acquired through a documentation study and data acquisition from the existing public sources. The data was obtained by downloading it directly from the international public data repository platform Mendeley Data on February 16, 2026, under the official title "Dataset Stunting and Nutritional Status of Toddler from Jeneponto Regency, South Sulawesi, Indonesia" [21], compiled by Asmaul Husna RS and a research team from Universitas Negeri Makassar. The acquisition procedure and data source documentation were carried out by searching the relevant repository, filtering the file format to Microsoft Excel (.xlsx), and downloading the raw data to local storage. This dataset was selected based on inclusion criteria highly relevant to the analytical needs of the research, where its variable attributes directly relate to the problem formulation regarding stunting prevention and toddler nutritional status assessment. Furthermore, exclusion criteria and subsequent data cleaning were applied during the preprocessing stage to filter out records failing standard physiological toddler thresholds. The initial sample size of 40,071 data records is considered sufficient and adequate to train machine learning models, supported by the high credibility of the academic data source.

C. Data Processing

The data pre-processing stage was carried out systematically and in stages to ensure that all raw data was optimally ready for use in machine learning modeling.

1. Data Loading and Variable Initialization

The initial stage of data pre-processing began with loading the main dataset sourced from the Jeneponto Regency data recapitulation, with an initial total of 40,071 toddler data records. The system then grouped the data columns into three main categories, namely input features (which include gender, age in months, weight, and height), predictive target variables, and Z-score supporting variables. Additionally, at this stage, a label mapping dictionary (Encoding Map) based on WHO standards was initialized to convert numerical codes into descriptive text labels of nutritional status.

2. Data Quality Checking

After the data was loaded, a comprehensive data quality check was performed on all 40,071 rows of data to detect the presence of missing values, duplicate data rows, and to validate the suitability of data types in each column. From this check, variations in writing formats were identified, as well as several clinical or formatting anomalies in certain columns, such as the appearance of the "#NUM!" string in the age column. The initial analysis also indicated a quite significant class imbalance ratio in the stunting nutritional status target variable.

No.	Gender	Age (Month)	Weight	Height	Weight for Age	Z-Score W/A	Height for Age	Z-Score H/A	Weight for Height	Z-Score W/H
1	F	54	13.2	97.5	Normal	-1.94	Stunted	-2.11	Normal	-0.95
2	M	44	12	92	Normal	-1.92	Stunted	-2.22	Normal	-0.88
...	...	...	...	...	...	...	...	...	...	...
40071	M	13	9.7	70	Normal	-0.33	Stunted	-3.19	Normal	1.67

Fig. 1. Sample dataset of stunting and toddler nutritional status from Jeneponto Regency, South Sulawesi, Indonesia.

Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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3. Data Cleaning

Based on the findings in the quality checking stage, a data cleaning process was carried out to correct the existing anomalies. The first step involved converting the age data type to numeric in order to clean 2 rows containing the "#NUM!" format error, which were subsequently deleted. Furthermore, the handling of missing values in the 'Weight for Height' column for 12 rows (0.03%) was done by substituting the mode value (Normal category = 2). After removing 4,288 duplicate data rows (10.70%), filtering was performed on 63 rows (0.16%) containing clinical anomalies based on the standard physiological thresholds for toddlers (age < 0 or > 59 months, weight < 1.5 kg or > 35 kg, and height < 40 cm or > 130 cm). In addition, 177 extreme outlier samples (0.44%) in the Z-score values were removed using the Interquartile Range (IQR) method with boundaries of Q1-3×IQR and Q3+3×IQR. Subsequently, rows with single label combinations were filtered out = 1. This series of cleaning processes produced 35,540 clean data records (88.69% of the raw data).

4. Data Exploration and Visualization

The statistical characteristics and data distribution patterns were then visualized in depth to understand the trends within the dataset. Furthermore, the characteristics and data distribution of the target variables were visualized to comprehend the level of class imbalance within the dataset. The frequency distribution of the target categories for each nutritional status indicator is displayed using a bar chart in Fig 2.

5. Feature Preparation

In the feature preparation stage, the independent feature matrix, which includes physical and demographic attributes, was strictly separated from the target label matrix. All values in the target columns were then converted into an integer format to meet the input format compatible with machine learning algorithms. Although nutritional status category labels are methodologically derived through deterministic rules based on WHO anthropometric standards using the variables of age, weight, and height, the deep learning architecture was designed to explore complex and non-linear multivariate interactions. By utilizing additional variables (such as gender) as well as the characteristics of the local empirical data distribution from Jeneponto Regency, the TabNet architecture is capable of learning adaptive clinical probability representations, enabling the model to capture meaningful variations in clinical trends in the field rather than merely replicating rigid deterministic class boundary functions.

6. Dataset Splitting

The entire clean dataset, totaling 35,540 rows, was partitioned using a stratified sampling technique based on target class combinations to ensure that class distribution proportions were maintained across subsets. The data was divided into three distinct proportions: a Training Set at 60% (21,324 rows) for training model parameters; a Testing Set at 30% (10,662 rows); and an internal Validation Set at 10% (3,554 rows). This internal validation set was kept sterile and completely isolated from both training and hyperparameter tuning processes, serving specifically as an internal hold-out dataset to evaluate system performance during the final prototype testing phase.

7. Distribution Verification and Statistical Testing

To ensure the absence of bias due to the partitioning process, the class percentages in each Train, Test, and Validation subset were strictly verified. Formal statistical testing using the Chi-Square test was conducted to prove that the class distribution across the data parts did not differ significantly, yielding significance values that met the required threshold parameters.

8. Feature Scaling

Scaling was specifically applied to numerical features using StandardScaler so that they possess a mean of 0 and a standard deviation of 1. To prevent data leakage, the scaler parameters were exclusively learned (fit) from the training data, and then separately transformed to the testing and validation data. This stage also included an analysis of Feature Importance using the Random Forest algorithm.

9. Data Imbalance Handling

Based on the findings in the quality checking stage, the Synthetic Minority Over-sampling Technique for Nominal and Continuous features (SMOTE-NC) was applied exclusively to the Training Set to overcome class imbalance issues in datasets possessing mixed data

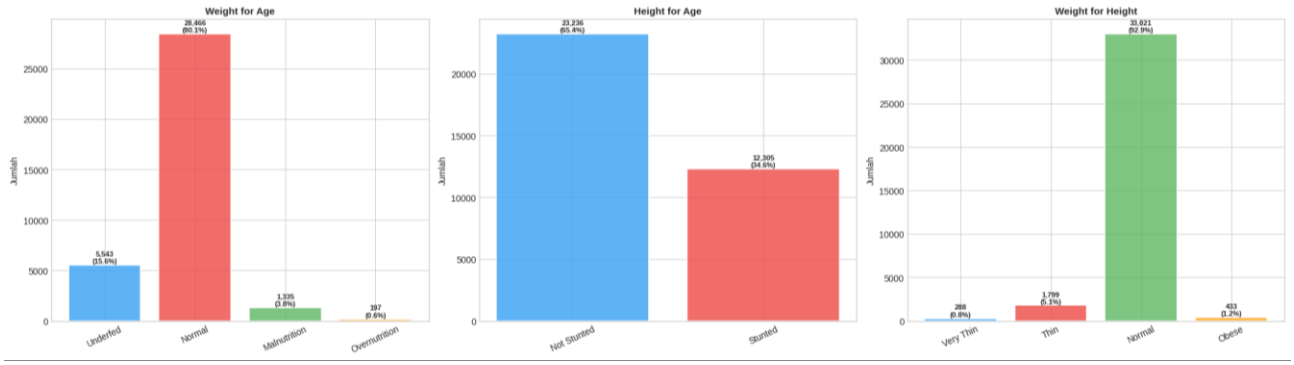


Fig. 2. Bar chart showing the distribution of data counts for each target variable category.

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types, namely categorical and continuous variables. The initial step of this algorithm is to identify and differentiate feature columns into a group of continuous features, such as age, weight, and height, and a group of nominal or categorical features, such as gender. Next, to find the nearest neighbors in the mixed data, the algorithm calculates a combined distance where continuous features are calculated using the Euclidean metric, while categorical features utilize a category difference penalty via the Heterogeneous Value Difference Metric.

Once the nearest neighbors are found, the algorithm generates continuous features through linear interpolation between the original sample and its neighbors, while for categorical features, the value is determined through a majority voting method. The new synthetic samples generated from this minority class are then merged into the training data. Prior to the application of SMOTE-NC, the number of data rows in the Training Set was 21,324 for each independent model trained separately for the three target indicators (Weight for Age, Height for Age, and Weight for Height) under skewed class distribution conditions. The SMOTE-NC algorithm was configured by explicitly defining the categorical feature index on the Gender column (0 = Female, 1 = Male), while continuous features (Age (Month), Weight, and Height) were calculated using the Euclidean metric, an HVDM penalty for categorical features, and a nearest neighbor parameter of k=5 with a consistent random state. After this hybrid oversampling process was executed exclusively on the Training Set, the total number of training data rows for each independent model increased to 85,851 rows, thereby producing an optimally regenerated class distribution leaving a controlled residual ratio without distorting the statistical structure of its original features.

10. Pre-processed Data Storage

As the final stage of the pre-processing sequence, all data subsets that had been cleaned, balanced, and standardized were saved into separate file formats, namely train_smote.csv, test.csv, and validation.csv, making them ready for direct execution in the core modeling stages.

D. Statistical Analysis

1. Distribution Verification and Statistical Testing

Distribution verification was implemented through a Chi-Square (χ^2) test of independence during the data splitting phase to evaluate class proportion consistency across subsets for all anthropometric target indicators, as detailed in Table 1. As presented in the table below, the cross-sectional comparisons across the *Weight for Age*, *Height for Age*, and *Weight for Height* indicators yielded extremely small test statistics close to zero alongside high p-values well above the significance threshold of $\alpha = 0.05$. These empirical metrics confirm that the categorical class proportions across all data partitions are highly consistent without any statistically significant differences, thereby accepting the null hypothesis (H_0), protecting the subsets from selection bias, and fully validating the homogeneity of class representation across the training, testing, and validation splits.

Table 1. Comprehensive Chi-Square (χ^2) statistic for class proportion verification across all data subsets.

Anthropometric Target Indicator	Subset Comparison	Chi-Square Test Statistic (χ2)	p-value
Weight for Age	Training vs Test	0.0019	1.0000
	Training vs Validation	0.0068	0.9999
	Test vs Validation	0.0073	0.9998
Height for Age	Training vs Test	0.0004	0.9834
	Training vs Validation	0.0000	0.9978
	Test vs Validation	0.0000	1.0000
Weight for Height	Training vs Test	0.0364	0.9982
	Training vs Validation	0.0158	0.9995
	Test vs Validation	0.0464	0.9974

2. Data Imbalance Handling Statistics

The initial class proportion analysis indicated a severe class imbalance ratio in the target variables, such as the W/A (Weight-for-Age) and H/A (Height-for-Age) indicators reaching more than a 100-fold difference. To overcome this obstacle, the Synthetic Minority Over-sampling Technique for Nominal and Continuous (SMOTE-NC) method was applied to precisely regenerate minority samples in data with mixed features. Post-resampling statistical verification proved that this method successfully reduced the imbalance ratio massively in each independent model without causing distortion in the original feature distribution. This reduction yielded a controlled residual ratio of 2.8× for the Weight for Age (W/A) indicator, down from the initial ratio of 144.8×, becoming 98.1% more balanced with a class distribution consisting of Class 0 (Underfed) with 23,064 samples (26.87%), Class 1 (Normal) with 32,035 samples (37.31%), Class 2 (Malnutrition) with 19,220 samples (22.39%), and Class 3 (Overnutrition) with 11,532 samples (13.43%); 1.5× for the Height for Age (H/A) indicator from an initial ratio of 1.9×, becoming 21.5% more balanced detailing Class 0 (Not Stunted) with 51,255 samples (59.70%) and Class 1 (Stunted) with 34,596 samples (40.30%); and 2.1× for the Weight for Height (W/H) indicator from an initial ratio of 115.2×, becoming 98.2% more balanced detailing Class 0 (Very Thin) with 15,376 samples (17.91%), Class 1 (Thin) with 19,220 samples (22.39%), Class 2 (Normal) with 32,035 samples (37.31%), and Class 3 (Obese) with 19,220 samples (22.39%). A visual comparison of the data

Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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distribution before and after handling using this method can be seen in Fig 3.

3. Probabilistic Hyperparameter Optimization

The optimal parameter search was conducted systematically through the Bayesian Optimization mechanism implemented using the Optuna library with the TPE (Tree-structured Parzen Estimator) sampler for 50 trials with a random seed = 42. The search-space boundaries set included: n_d [8–64], n_a [8–64], n_steps [3–10], gamma [1.0–2.0], and learning_rate [1e-4–1e-1]. The hyperparameter choices were evaluated using 5-fold cross-validation internally on the Training Set (21,324 samples). The Testing Set (10,662 samples) was used for the final comparative evaluation, while the Validation Set (3,554 samples) was kept as an unseen hold-out dataset completely isolated from both the parameter search and training processes. This objective function evaluation ensured that the deployed deep learning architecture configuration reached an optimal point objectively and avoided overfitting.

4. Diagnostic Performance Evaluation Metrics

Conceptually, evaluation or assessment can be defined as the process of concluding and interpreting facts and making basic professional judgments to form policies based on a set of information [22]. In the realm of machine learning, model evaluation is a stage conducted after the model is trained and tested, where its performance is measured using specific metrics to determine how well the model predicts or classifies data [23]. Methodologically, the performance evaluation of a classification model is measured using a Confusion Matrix approach, which extracts the truth value of predictions through quantitative metrics. Below is a breakdown of each evaluation metric used.

Confusion Matrix is a method for evaluating a machine learning model by comparing the predicted class with the actual class in empirical data [23]. This matrix evaluates performance based on the calculation of four basic components, namely True Positive (TP) as the number of positive class data correctly predicted as positive, True Negative (TN) as the number of negative class data correctly predicted as negative, False Positive (FP) as the number of negative class data incorrectly predicted as positive, and False Negative (FN) as the number of positive class data incorrectly predicted as negative.

Accuracy measures how accurately the model classifies the overall data, expressed as the ratio of correct predictions to the total amount of data [23]. Accuracy can be calculated using Eq. (1) as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Description: Acc is the overall accuracy value of the model's predictions, TP is True Positive, TN is True Negative, FP is False Positive, and FN is False Negative [23].

Precision measures the proportion of data predicted as positive that is actually positive out of all the data predicted as positive by the model [23]. A high precision means that when the model predicts a data point as positive, it is highly likely that the prediction is indeed correct [23]. Precision can be calculated using Eq. (2) as follows:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

Description: Prec is the model's precision value, TP represents true positive predictions, and FP represents the model's prediction errors where negative data is considered positive [23]. Recall measures how well the model detects and identifies the proportion of data predicted as positive that is actually positive out of all data that is in fact positive [23]. Recall can be calculated using Eq. (3) as follows:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

Description: Rec represents the model's sensitivity level, TP is the number of correctly predicted positive data, and FN is the number of positive data that failed to be detected because they were predicted as negative [23].

F1-Score is the harmonic mean of precision and recall, which serves to provide a level of balance between these two metrics [23]. This metric is used when the analysis considers an optimal balance between precision and

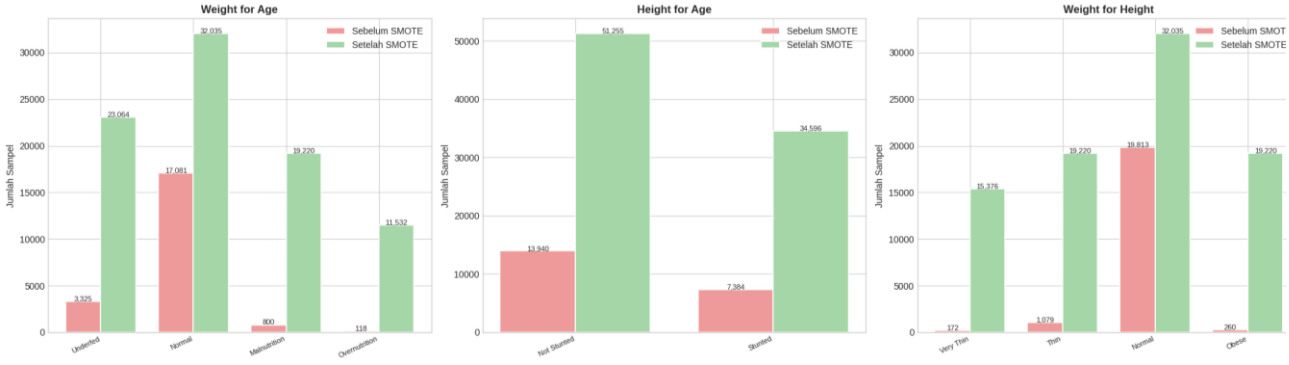


Fig. 3. Comparison chart of sample counts before and after the application of SMOTE-NC.

Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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sensitivity results [23]. F1-Score can be calculated using Eq. (4) as follows:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

Description: F1 represents the balance value of the model's performance. The Recall (sensitivity) and Precision values are taken from the previous calculations [23]. This comprehensive evaluation is also supplemented with a training performance curve to ensure the model's reliability as a clinical decision support instrument.

5. Model Performance Testing and Comparison

The comparative evaluation process was conducted between the Multilayer Perceptron (MLP) architecture, acting as the baseline model, against the TabNet architecture on the tabular toddler anthropometry dataset. The main objective of this comparative analysis was to objectively assess the significance of the predictive performance differences between the models in classifying the three standard nutritional status growth indicators. Based on the comprehensive evaluation results of the Multilayer Perceptron (MLP) and TabNet model architectures in the Training and Testing phases, quantitative performance encompassing accuracy, precision, recall, and f1-score.

III. RESULTS

A. Modeling with TabNet Architecture

Ultimately, the TabNet architecture was chosen because it is specifically designed to handle tabular data and is capable of integrating learning representation with good interpretability through sequential attention mechanisms and sparse feature selection. Technically, TabNet demonstrated superior generalization stability compared to the Multilayer Perceptron (MLP). This can be observed in detail in Table 2, where the hyperparameter optimization process using the Bayesian Optimization approach via the Optuna framework yielded optimal configurations along with their best performance scores for each model across all target indicators (*Weight for Age*, *Height for Age*, and *Weight for Height*). Building on these optimal parameters, the comprehensive performance evaluation of both models across the training and testing phases is fully detailed in Table 3. As shown in the table, TabNet exhibits exceptional generalization stability, evidenced by a very tight accuracy gap between the training and testing data such as 0.32% on the W/A indicator (Train: 0.9678, Test: 0.9646) compared to 1.60% on the MLP model (Train: 0.9833, Test: 0.9673) along with the evaluation scores from Table 3 remaining consistently above 0.94 across all evaluation scenarios. This comprehensive evaluation metric approach was chosen to accurately account for class support proportions given the data distribution characteristics. Although the training and hyperparameter optimization were carried out independently for each target indicator, the GiziLens software architecture designed an integrated inference mechanism on the backend. When a health worker inputs a set of toddler anthropometric data through the web interface, the system automatically executes the three models concurrently, so that the classification results for W/A, H/A, and W/H can be presented simultaneously in a single input process.

Table 2. Details of Hyperparameter Optimization Results and Best Weighted F1 Values for MLP and TabNet Models

Model	Target Indicator	Hyperparameter / Best Metric	Value
MLP	Weight for Age	Best Weighted F1	0.9644
		n_layers	3
		n_units_10	480
		n_units_11	128
		n_units_12	288
		learning_rate	0.002714724944320898
		dropout	0.1
		activation	relu
		weight_decay	3.715601701713681e-05
	Height for Age	Best Weighted F1	0.9596
		n_layers	3
		n_units_10	128
		n_units_11	480
		n_units_12	288
		learning_rate	0.005125266198304279
		dropout	0.0
		activation	relu
		weight_decay	1.6172056640175367e-06
	Weight for Height	Best Weighted F1	0.9835
		n_layers	3
		n_units_10	32
		n_units_11	512
		n_units_12	448
		learning_rate	0.0004335281794951569
		dropout	0.1
		activation	elu
		weight_decay	1.9762189340280066e-05
TabNet	Weight for Age	Best Weighted F1	0.9630
		n_d	64
		n_a	32
		n_steps	5
		gamma	1.0
		learning_rate	0.0011026511314900513

Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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		momentum	0.200845171 50524542
	Height for Age	Best Weighted F1	0.9584
		n_d	64
		n_a	32
		n_steps	7
		gamma	1.0
		learning_rate	0.011076376 28638944
		momentum	0.267161878 995188
	Weight for Height	Best Weighted F1	0.9826
		n_d	64
		n_a	48
		n_steps	4
		gamma	1.3
		learning_rate	0.003099246 938221805
		momentum	0.277346797 1702844

Table 3. Summary of performance including Accuracy, Precision, Recall, and F1-Score values for MLP and TabNet models in the Training and Testing phases.

Model	Target	Fase	Accuracy	Precision	Recall	F1-Score
MLP	W/A	Train	0.9833	0.98	0.98	0.9833
		Test	0.9673	0.97	0.97	0.9676
	H/A	Train	0.9813	0.98	0.98	0.9812
		Test	0.9607	0.96	0.96	0.9604
	W/H	Train	0.9482	0.95	0.95	0.9482
		Test	0.9838	0.98	0.98	0.9837
TabNet	W/A	Train	0.9678	0.97	0.97	0.9677
		Test	0.9646	0.97	0.96	0.9649
	H/A	Train	0.9721	0.97	0.97	0.9721
		Test	0.9588	0.96	0.96	0.9586
	W/H	Train	0.9748	0.98	0.97	0.9748
		Test	0.9811	0.98	0.98	0.9816

B. GiziLens Information System Implementation

The implementation of the GiziLens Information System was designed as a web-based application that utilizes technology to distribute healthcare services and information flexibly and in real-time [24],[25]. This system was built using the Python programming language, which is supported by simple syntax and a vast ecosystem of libraries for handling complex logic and AI modeling [26]. As the main back-end framework, GiziLens utilizes the Flask micro-framework, which implements the Model-View-Controller (MVC) architectural pattern [27]. This architecture connects the web browser interface with relational database management via MySQL and phpMyAdmin to store toddler medical history, staff authentication, and classification result history in a structured manner. To support the entire software development life cycle, Visual Studio Code was used as the primary code editor, Docker & Docker Compose as the containerization platform to ensure the application can run consistently in any environment, and Figma and Draw.io for designing the UI/UX interface and system flowcharts. Operationally, the back-end section manages server logic, AI inference model execution, and database operations, while the front-end section utilizes Jinja2 templates and HTML/CSS to present information dynamically and responsively. The GiziLens application is equipped with comprehensive functional features, including the Login Page, Dashboard, Examination Input Page, Growth Chart Page, Examination History Page, Batch Upload, Export to Excel & PDF Page, Model Information Page, and Staff Management. To provide a clearer overview, Fig 4 shows a visual display of the GiziLens web-based application interface.

As a foundation for data design architecture, this system is described through a conceptual design starting from a hierarchy diagram to a Data Flow Diagram (DFD), as shown in Fig 5. This comprehensive visual representation carefully maps all basic information pathways to ensure smooth and robust operational functionality.

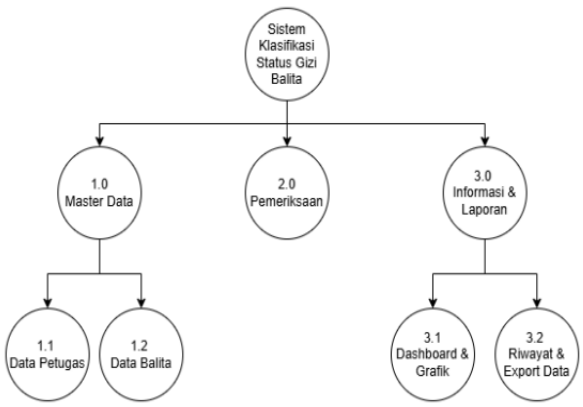


Fig. 5. Data Flow Diagram of the main processes in

Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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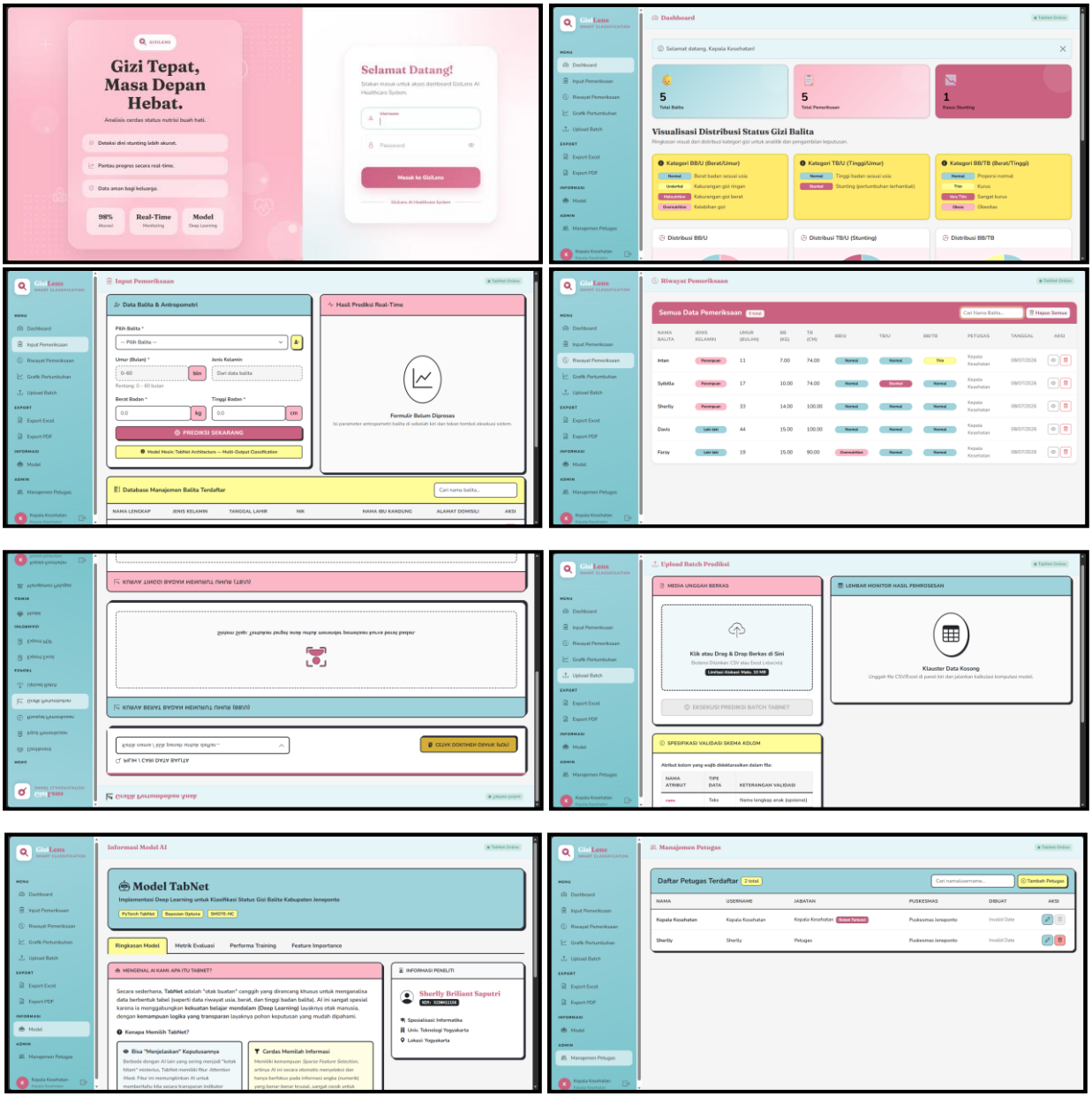


Fig. 4. Visual display showing the interface of the GiziLens web-based application.

the toddler nutritional status classification system.

Based on the Hierarchy Diagram, the system is decomposed at the first level into three main processes: Master Data (1.0), Examination (2.0), and Information & Reporting (3.0). At the second level, these main processes are broken down into more specific sub-processes except for the standalone Examination process (2.0), which include Staff Data (1.1) and Toddler Data (1.2) under Master Data, as well as Dashboard & Graphics (3.1) and History & Data Export (3.2) under Information & Reporting. This design then proceeds to DFD Level 0, or context diagram, which maps the direct interaction between external entities (Staff) and the Toddler Nutritional Status Classification System. As a visual instrument illustrating information movement, a DFD is highly effective for mapping information flow and systematically revealing data processing and storage activities [28],[29]. Through this context diagram, the staff provide inputs in the form of User Data (specifically for the Head of Health), Toddler Data, Examination Data, and Batch File Data, while the system returns outputs in the form of related data information, classification reports, summary charts, and examination history. This data flow is further elaborated through DFD Level 1, which details the interaction between the Staff entity and the four main data stores, namely staff, toddler, examination, and

Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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classification_results via the three main processes. Furthermore, operational decomposition is detailed through DFD Level 2 Process 1, which sets the management of Staff Data (1.1) and Toddler Data (1.2) in related data stores, as well as DFD Level 2 Process 3, which breaks down reporting into the Dashboard & Graphics (3.1) and History & Data Export (3.2) sub-processes to comprehensively gather information from all system data stores.

To understand the sequential operational workflow, the system design is equipped with Fig 6**,** flowchart illustrating the logical stages from beginning to end. A flowchart is a graphical representation of algorithms and informative procedures that function to visualize logical flow systematically through the use of standard symbols before being translated into a programming language [30],[31]. The main workflow begins when a staff member enters credentials on the login page to be validated by the system before accessing the main dashboard. The staff member can then input specific toddler metric data on the examination menu to automatically generate nutritional status prediction outputs, review history details on the history menu, and print exportable report documents. Outside the examination workflow, system operational integrity is maintained through a staff management flowchart, which regulates access rights based on position. Upon successful login, the system verifies whether the staff member acts as the Head of Health; if not, the staff management menu is hidden, whereas the Head of Health is given full access to add, edit, or delete staff data, with automatic protection canceling any deletion attempts if the target account holds the position of Head of Health.

The physical database design stage is represented through an Entity Relationship Diagram (ERD) to visually map the functional relationships between basic objects. An ERD is a tool used to visually design and model data during the project requirements analysis stage, facilitating developers in understanding existing data structures and flows [22]. The main entities in this system include "Staff" as users, "Toddlers" as examination subjects, and "Classification Results" which store model outputs, where their interaction is bridged by the examination process that periodically records anthropometric data. This database structure is explained in detail in the relational table schema specifications. The "Staff" table has a one-to-many relationship with the "Examination" table. The "Toddler" table functions to store child identities and also has a one-to-many relationship with the "Examination" table. The "Examination" table acts as the main transaction table recording examination time, age in months (age_months), weight, height for high precision levels, and staff notes, with a many-to-one relationship to the "Toddler" and "Staff" tables, and a one-to-one connection with the "Classification Results" table. Lastly, the "Classification Results" table is designed to store the analytical outputs of the Deep Learning model. To test functional validity, latency performance, failure handling, and the reliability of all designed modules ranging from Head of Health access control, TabNet model inference, to mass data management and reporting, comprehensive system testing was conducted as summarized in Table 4.

C. Validation Data Analysis

The entire clean dataset, totaling 35,540 rows, was partitioned using a stratified sampling technique based on target class combinations to ensure that the proportion of class distribution was maintained in each segment. Based on the research design, the data was divided into three main proportions: a Training Set of 60% consisting of 21,324 rows allocated to train the model parameter patterns, a Testing Set of 30% consisting of 10,662 rows for final performance evaluation, and a Validation Set of 3,554 rows specifically allocated as sterile hold-out data for final inference testing post-modeling.

Although both the TabNet and MLP architectures demonstrated competitive performance metrics with relatively narrow accuracy gaps (as detailed in Table 2),

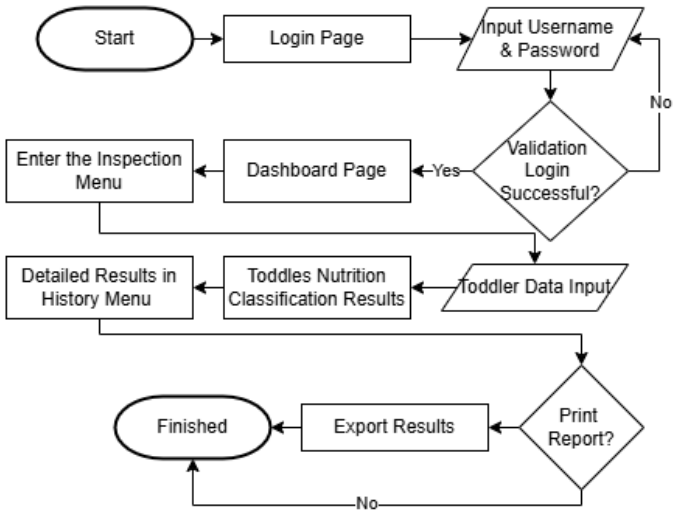


Fig. 6. Flowchart illustrating the process of the toddler nutritional status classification system.

Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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Table 4. Testing scenarios and functional evaluation of the GiziLens system to ensure the reliability of all application modules.

Feature / Testing	Initial Condition	Scenario	Expected Result	Conclusion
Role Access Control	Logged in with a Nutrition Officer account.	Accessing the Staff Management menu.	System denies access & hides the menu.	As Expected
Staff Management	Logged in with a Head of Health account.	Adding/updating staff data.	Staff data is saved in the database.	As Expected
Main Dashboard	User is logged in.	Opening the main page (Dashboard).	Displays statistical summaries & metrics.	As Expected
TabNet Inference	On the Examination Input form.	Inputting anthropometric data & clicking predict.	Nutritional classification appears in < 0.5 seconds.	As Expected
Growth Chart	Opening child history details.	Accessing the "Growth Chart" menu.	Z-score trend chart is rendered dynamically.	As Expected
Medical Record History	On the History menu.	Searching/filtering examination data.	Displays a complete chronological list.	As Expected
AI Model Information	Opening the Model Information panel.	Reviewing model specification details.	Displays TabNet specifications & performance.	As Expected
Validation & Error Handling	Opening the examination input form.	Entering negative / unreasonable data.	System rejects the input & displays a flash message.	As Expected
Mass Data Upload	On the Batch Upload menu.	Uploading a CSV/Excel document.	Data is mass-processed into the database.	As Expected
Report Export	On the Reports/History menu.	Downloading Excel & PDF formats.	The file is downloaded with a neat layout.	As Expected

concluding model superiority must not rely solely on marginal accuracy differences. The unique characteristics of the large-scale Jeneponto toddler anthropometric dataset exhibit minority class distributions susceptible to distortion, making the application of the SMOTE-NC resampling technique critical for preserving categorical class proportions and mitigating prediction bias toward minority classes such as severe acute malnutrition.

When compared critically against the existing literature in healthcare tabular classification, conventional deep neural networks frequently encounter overfitting or struggle to capture complex non-linear feature interactions. Conversely, TabNet excels through its sequential attention mechanism, which performs automated sparse feature selection, enabling the model to concentrate exclusively on the most relevant anthropometric indicators (*Weight-for-Age*, *Height-for-Age*, and *Weight-for-Height*).

Furthermore, comprehensive system functional testing presented in Table 3 demonstrates that this performance reliability extends beyond offline experimentation into stable integration within the GiziLens backend workflow. Evaluation using the isolated validation hold-out set of 3,554 samples strictly sequestered and never exposed to training or Optuna hyperparameter optimization revealed robust generalization accuracy rates of 97% for *Weight-for-Age* (W/A), 96% for *Height-for-Age* (H/A), and 98% for *Weight-for-Height* (W/H), as summarized in Table 5. These findings confirm that TabNet's performance stability is driven by its architectural resilience against unseen data, verifying the system's operational readiness for deployment in public health centers (Puskesmas) or integrated healthcare posts (Posyandu).

Table 5. Comparison of TabNet architecture accuracy levels in training, testing, and validation phases for each nutritional status indicator.

Model	Target	Training Phase	Testing Phase	Validation Phase
TabNet	W/A	0.96	0.96	0.97
TabNet	H/A	0.97	0.95	0.96
TabNet	W/H	0.97	0.98	0.98

IV. DISCUSSION

A. In-depth Interpretation of TabNet Model Performance and the GiziLens System

B.

Based on the evaluation results in Table 3 and Table 6, the Multilayer Perceptron (MLP) recorded a slightly higher absolute testing accuracy on the W/A indicator (96.73%

Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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Table 6. Comparison of per-class evaluation metrics between the MLP and TabNet architectures in the training and testing phases.

Target	Category	Model	Precision (Train)	Recall (Train)	F1-Score (Train)	Precision (Test)	Recall (Test)	F1-Score (Test)	Support (Train / Test)
W/A	Underfed	MLP	0.98	0.97	0.97	0.91	0.90	0.91	23.064 / 1.663
		TabNet	0.95	0.94	0.95	0.91	0.88	0.90	23.064 / 1.663
	Normal	MLP	0.99	0.99	0.99	0.99	0.98	0.98	32.035 / 8.539
		TabNet	0.98	0.98	0.98	0.98	0.98	0.98	32.035 / 8.539
	Malnutrition	MLP	0.98	0.98	0.98	0.87	0.94	0.90	19.220 / 401
		TabNet	0.97	0.95	0.96	0.84	0.95	0.89	19.220 / 401
	Overnutrition	MLP	0.99	1.00	0.99	0.62	0.93	0.75	11.532 / 59
		TabNet	0.98	0.99	0.99	0.67	0.93	0.78	11.532 / 59
H/A	Not Stunted	MLP	0.98	0.99	0.98	0.96	0.99	0.97	51.255 / 6.972
		TabNet	0.98	0.98	0.98	0.96	0.98	0.97	51.255 / 6.972
	Stunted	MLP	0.99	0.96	0.98	0.97	0.91	0.94	34.596 / 3.690
		TabNet	0.96	0.97	0.97	0.96	0.92	0.94	34.596 / 3.690
W/H	Very Thin	MLP	1.00	0.86	0.92	0.91	0.70	0.79	15.376 / 88
		TabNet	0.99	0.94	0.97	0.87	0.82	0.84	15.376 / 88
	Thin	MLP	0.88	0.95	0.91	0.85	0.89	0.87	19.220 / 540
		TabNet	0.93	0.97	0.95	0.80	0.92	0.86	19.220 / 540
	Normal	MLP	0.94	0.99	0.97	0.99	0.99	0.99	32.035 / 9.905
		TabNet	0.98	0.98	0.98	1.00	0.99	0.99	32.035 / 9.905
	Obese	MLP	1.00	0.95	0.97	0.93	0.86	0.90	19.220 / 129
		TabNet	1.00	1.00	1.00	0.83	0.94	0.88	19.220 / 129

vs 96.46%) and W/H (98.38% vs 98.11%). However, concluding model superiority must not rely solely on marginal accuracy differences. When evaluated against the unique characteristics of the large-scale Jeneponto toddler anthropometric dataset which exhibits minority class distributions highly susceptible to distortion and clinical noise the TabNet architecture was selected because its performance is underpinned by a rigorous stratified 3-way data splitting strategy and robust generalization stability. TabNet's superiority is indicated by the smaller accuracy gap between the training and testing data (0.32% vs 1.60% for W/A; 1.33% vs 2.06% for H/A; and -0.63% vs -3.56% for W/H), showing lower variance against the risk of overfitting. It should be noted that this comparison reflects repeated generalization behavior. This stability indicates that TabNet has lower variance and is robust against the risk of overfitting when processing new clinical data. Theoretically, this stability aligns with the design of the sequential attention mechanism in TabNet, which adaptively selects features

Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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in tabular data. Although specific ablation testing for the attention component was not conducted in this study, the characteristics of the architecture provide a plausible interpretation regarding TabNet's ability to reduce the correlation of less relevant features.

Regarding the potential for target leakage and clinical

This success also aligns with the characteristics of deep learning, which extracts data representations hierarchically and automatically through non-linear transformations to minimize the risk of bias, where this technology is highly optimal in identifying complex patterns in health information to achieve maximum

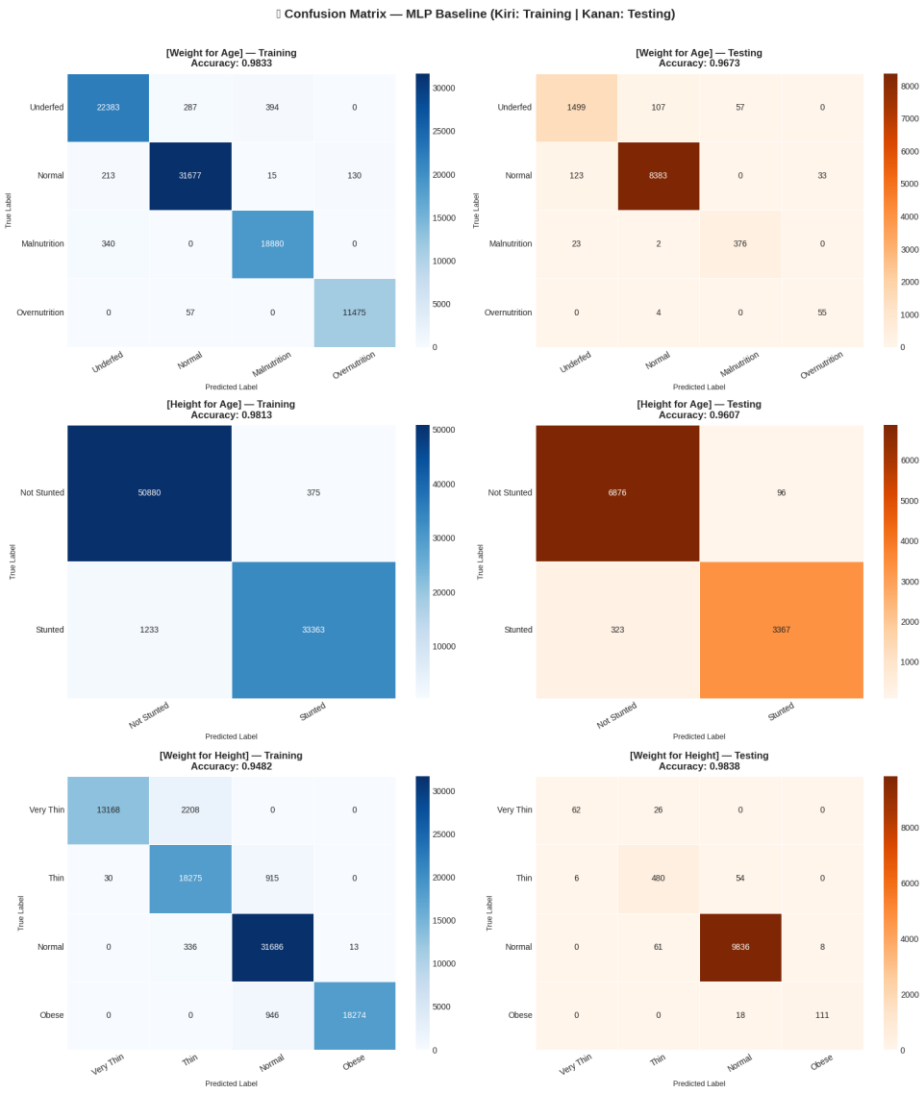


Fig. 7. Confusion Matrix of Training and Testing Performance - Baseline MLP Model on Three Nutritional Status Parameters (W/A, H/A, and W/H).

redundancy between input features (age, weight, height) and nutritional status labels derived from WHO standards, it must be emphasized that this modeling process does not function merely as a lookup table. WHO growth standards establish continuous and dynamic Z-score thresholds relative to age, where the TabNet model explores high-dimensional feature interaction relationships through an attention mechanism capable of adaptively identifying feature importance weights amidst complex field data variations. This proves that the model learns empirically meaningful clinical probability patterns, going beyond basic deterministic rule boundaries.

accuracy in medical analyses requiring deep precision [32],[33]. Furthermore, the successful handling of class imbalance using SMOTE-NC proved crucial in saving the model from majority bias, considering the phenomenon of class imbalance (imbalanced data) where the number of positive class samples is significantly fewer than the negative class, which can cause the model to tend to only learn dominant patterns and ignore minority classes [32].

By reducing the imbalance ratio where the W/A indicator, which initially reached more than 144.8x, was successfully reduced significantly to 2.8x, and the H/A indicator from 1.9x to 1.5x in a hybrid manner, the model

Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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can recognize toddler growth deviations more objectively. The evaluation of this prediction distribution is further validated through the visualization of the Confusion Matrix on the Baseline MLP and TabNet models to observe the classification performance in each class in detail, including the minority categories which can be seen in Fig 7 and Fig 8.

To present the model performance evaluation in more detail for each category, Table 6 presents a complete recapitulation of per-class evaluation metrics (precision, recall, and F1-score) for the Baseline MLP and TabNet architectures in the training and testing phases. Based on the confusion matrix visualization results (Fig 7and Fig 8) and the details in Table 6, it is clear that the model is capable of distributing predictions with a high degree of accuracy, both in majority and minority categories. This is evidenced by the recall achievements remaining high in critical minority classes, such as Malnutrition (0.95), Overnutrition (0.93), Stunted (0.92), and Very Thin (0.82) in the TabNet model. These findings confirm the stability of the model's generalization without indications of extreme overfitting, simultaneously proving that the model does not experience bias toward the majority class.

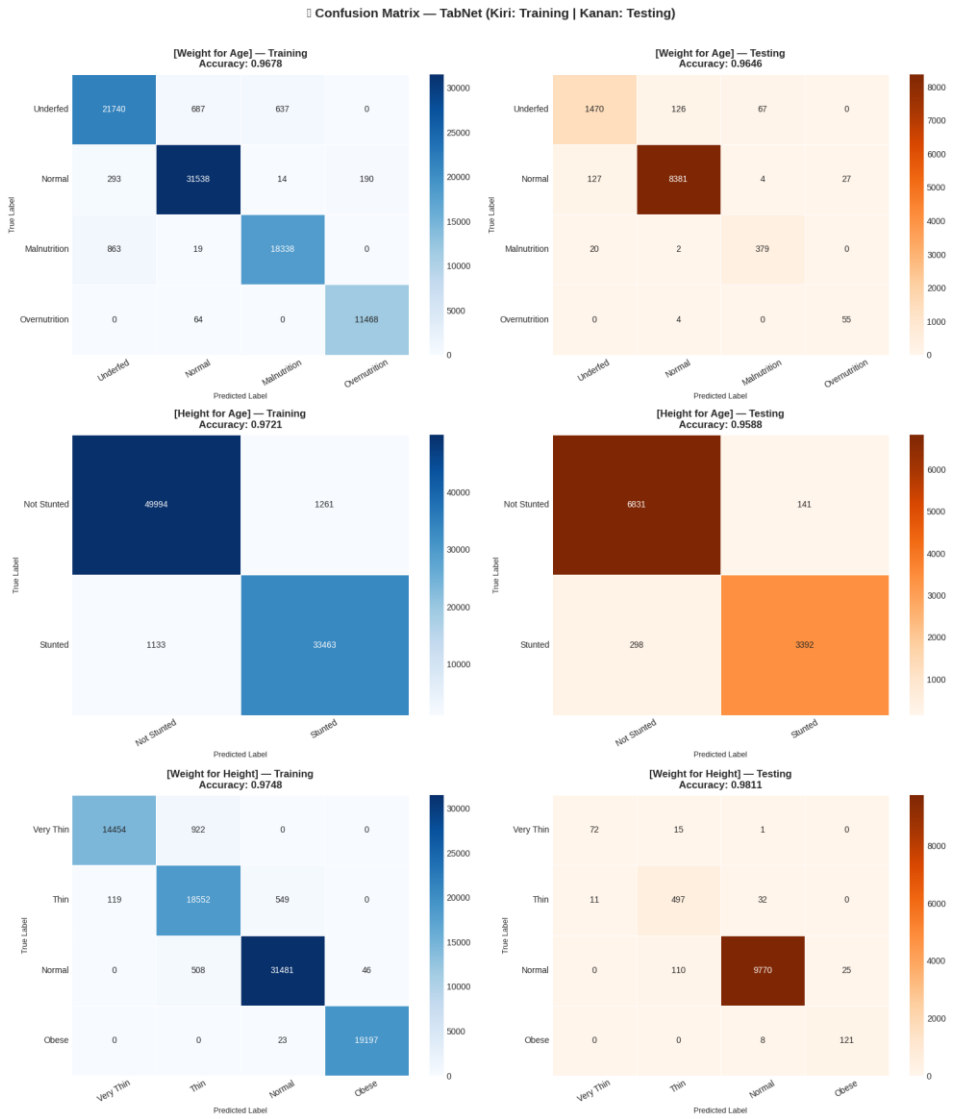


Fig. 8. Confusion Matrix of Training and Testing Performance of the TabNet Model on Three Nutritional Status Parameters (W/A, H/A, and W/H).

From an implementation perspective, integrating this best-performing model into the GiziLens web application through the Flask micro-framework translates complex deep learning computations into an interactive Decision Support System (DSS) interface. This is in line with the concept of a DSS, which is designed to produce reliable and accurate decisions in handling real-world problems [33]. The consistent validation results with high accuracy demonstrate the potential for the system's technical reliability. Therefore, this prototype is viable to proceed to the prospective field trial stage with healthcare workers

Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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before being considered for full-scale operational adoption in child nutrition monitoring and early stunting detection [34].

B. Comparative Analysis of Model Performance with Similar Studies

The performance findings of this study were validated by comparing them with various cutting-edge literature approaches in the domain of toddler nutritional status classification and stunting. Based on previous studies, modeling using Decision Tree C4.5 based on Z-score was only able to achieve an accuracy rate of 61.82% in identifying stunting [7]. This approach subsequently evolved with the implementation of Deep Neural Networks (DNNs), which were able to achieve an accuracy of 93.83% due to their reliability against noise [8]. Meanwhile, another study combining Extreme Gradient Boosting (XGBoost) with Bayesian Optimization and an oversampling technique recorded an accuracy of up to 98.2% [10]. When compared to these studies, the TabNet model proposed in this research not only competes in terms of quantitative accuracy but also offers advantages in the interpretability of its attention mechanism as well as practical deployment through the GiziLens application. This constitutes a major differentiator because the majority of previous studies remained purely algorithmic (standalone) without being integrated into an operational web ecosystem to support regular child anthropometry monitoring [35].

C. Limitations and Weaknesses of the Study

Although the achieved results have met the target functional and accuracy performance, this study has several methodological and technical limitations that need to be noted. The first limitation relates to the reliance on secondary data quality sourced exclusively from medical records in Jeneponto Regency for the period 2021–2024, where model validity heavily depends on the accuracy of anthropometric recording at the Posyandu level, meaning potential human errors during manual field measurements and unrecorded socio-explanatory factors cannot be completely eliminated. The second limitation concerns the geographical coverage of the training dataset, which focuses strictly on a single region without evaluating an independent geographical dataset, relying instead on a rigorous internal validation approach; consequently, the reported accuracy level purely reflects internal performance on regional data characteristics rather than nationwide generalization across the Indonesian population. External testing using data from various regencies or provinces is highly recommended for future model evaluation. The third limitation involves the potential for target leakage and clinical redundancy due to the direct dependency between input features (age, weight, height) and nutritional status labels derived deterministically from WHO Z-score standards; although the model learns multivariate probability patterns, this structural overlap acts as a limiting factor on the complexity of learned relationships. The fourth limitation is the current absence of prospective or clinical validation directly within real-world healthcare settings involving medical professionals for operational decision-making. The fifth limitation concerns training computational complexity, as the integration of the TabNet Deep Learning architecture, Optuna Bayesian Optimization with TPE, and SMOTE-NC oversampling on large-scale datasets demands substantial computational resources, while synthetic samples generated via oversampling may not fully capture complex real-world clinical variations.

D. Implications of the Research

The study and development of the GiziLens system provide significant implications, both theoretically and practically, for the fields of health and technology. Theoretically or academically, this research enriches the literature on software engineering and artificial intelligence by proving that the TabNet architecture is highly effective when applied to tabular anthropometric data, while validating the effectiveness of the hybrid combination between SMOTE-NC and Optuna in reducing bias caused by imbalanced medical data classes [32]. This research also strengthens the understanding that linear growth failures categorized as stunting a chronic condition resulting from long-term malnutrition below -2 Standard Deviations (SD) based on WHO curves [2] can be simultaneously mapped with the Weight-for-Age (W/A), Height-for-Age (H/A), and Weight-for-Height (W/H) indices. Practically, the GiziLens application facilitates healthcare workers at Public Health Centers (Puskesmas) and Integrated Healthcare Posts (Posyandu) to transition from fragmented manual diagnosis methods. The system provides accurate and simultaneous diagnostic instruments, thereby supporting the optimization of nutritional status during the golden period of children, and assists the Health Office in accelerating the formulation of targeted stunting prevention intervention policies based on data (data-driven decision making).

V. CONCLUSION

This study aimed to evaluate the effectiveness of data imbalance handling using the SMOTE-NC technique, compare empirical performance between the TabNet and Multilayer Perceptron (MLP) deep learning architectures in classifying three primary nutritional status indicators (Weight-for-Age, Height-for-Age, and Weight-for-Height), analyze the impact of Optuna-based hyperparameter optimization, and develop the "GiziLens" web-based application as a reliable Decision Support System (DSS) for healthcare practitioners.

Based on empirical comparisons, the TabNet architecture was selected and integrated into the GiziLens system because it demonstrated superior generalization stability compared to MLP, featuring a tighter train-test

Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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accuracy gap (0.32% for Weight-for-Age, 1.33% for Height-for-Age, and -0.63% for Weight-for-Height). Furthermore, the application of SMOTE-NC successfully mitigated class imbalance reducing the imbalance ratio from over 144.8x down to 2.8x for Weight-for-Age, 1.9x to 1.5x for Height-for-Age, and 115.2x to 2.1x for Weight-for-Height while the integration of Bayesian Optimization through the Optuna framework efficiently determined parameters without blind searching [20],[36]. Powered by this TabNet model, the GiziLens web prototype proved technical feasibility and achieved robust internal validation performance with accuracy rates reaching 97% for Weight-for-Age, 96% for Height-for-Age, and 98% for Weight-for-Height.

As a retrospective prototype based on regional data from Jeneponto Regency, this system cannot yet be claimed as a nationally ready-to-use clinical diagnostic tool. Future development must prioritize external validation on multi-regional datasets across various regencies or provinces in Indonesia, subgroup analyses, prospective evaluations within healthcare facilities, model calibration, and comprehensive usability testing alongside medical personnel.

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Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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AUTHOR BIOGRAPHY



Sherlly Briliant Saputri is an undergraduate student in Informatics at the Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Indonesia. She was born on September 15, 2005, in Bandung, West Java. Her academic interests include web-based software development and intelligent systems. Since enrolling as an Informatics student in 2023, she has been involved in various course projects focused on developing website-based digital platforms. She is interested in applying deep learning technology to support health and efficient data management. Furthermore, she has a strong interest in functional and aesthetic interface design to enhance the user experience.



Ledy Elsera Astrianty Ledy Elsera Astrianty, born in Klaten on March 12, 1994, is an academic and informatics researcher who earned her Bachelor's degree in Informatics Engineering (Intelligent Systems) from Universitas Teknologi Yogyakarta (UTY) in 2016 and her Master's degree in Informatics (Medical Informatics) from Universitas Islam Indonesia (UII) in 2019. She focuses her expertise on Health Application Development and Medical Statistics. As an educator, she actively teaches core and applied courses, including E-Health, Medical Data Exchange, Health Ethics and Legal Aspects, Clinical Decision Support Systems, Data Science, Machine Learning, and Web and Mobile Application Development. Her research and community service focus on digital health innovation, artificial intelligence, and community empowerment. She is a recipient of the Kemendikbudristek PDP Grant (2022 & 2023) for an infant birth weight estimation system and postpartum depression screening, as well as the Kemdiktisaintek Community Partnership Empowerment Grant (2026) for the implementation of Mobile-AR in Gunungkidul.

Corresponding author: Ledy Elsera Astrianty, ledyelsera@uty.ac.id, Faculty of Science and Technology, Universitas Teknologi Yogyakarta, Jl. Siliwangi (Ringroad Utara), Jombor, Sleman, Yogyakarta 55285, Indonesia.

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