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Research Article

Keywords: Malnutrition, WAZ, HAZ, WHZ, MUAC, Machine Learning, SHAP, LIME

Posted Date: May 8th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-7410572/v1

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Additional Declarations: No competing interests reported.

Towards Early Detection of Pediatric Malnutrition in Chittagong Region: A Stacked Ensemble and XAI-Based Study

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Abstract

Malnutrition can be a significant issue in a developing country like Bangladesh. Weight-for-Age Z-score (WAZ), Height-for-Age Z-score (HAZ), Weight-for-Height Z-score (WHZ), and Mid-Upper Arm Circumference (MUAC) are standard anthropometric measures used to assess the nutritional health of children under five. The dataset used in this study was collected from two districts (Noakhali and Lakshmipur) in the Chittagong region and is employed to explore machine learning models for predicting pediatric nutritional status. Several supervised machine learning models, including Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Multilayer Perceptron (MLP), are implemented in this research. A stacking ensemble model is developed by combining three classifiers, such as DT, MLP, and LR, to improve classification performance. The preprocessing techniques used to remove outliers and missing values, scale features, and SMOTE were used to balance the classes, which led us to evaluate the models' performance with metrics including F1-score, accuracy, recall, and precision. The Stacking Classifier achieved an accuracy of 99.00%, an F1-score of 97.77%, and an AUC of 99%, surpassing all other models. This analysis demonstrates excellent reliability as it consistently and accurately predicts malnutrition status. Additionally, explainability AI techniques such as SHAP and LIME were used to understand feature contributions and interpret model predictions. By integrating data, these findings suggest that machine learning can effectively support population monitoring and help develop tailored dietary plans in resource-limited environments. Furthermore, a web-based API was created to utilize the stacked classifier for estimating malnutrition levels.

Keywords: Malnutrition, WAZ, HAZ, WHZ, MUAC, Machine Learning, SHAP, LIME.

1. Introduction

Undernutrition is a critical issue of global public health challenge that leads to excessive death and total disease burden and is prevalent among children under five, especially in low and middle-income nations [1]. It not only influences physical development but also undermines cognitive progress, depresses immune response, and kills productivity in the future [2]. UNICEF declares that chronically undernourished children have higher chances of being underachievers academically and economically in their future lives. Under-five malnutrition is also widespread in both Sub-Saharan Africa and South Asia. Proper interventions and data-oriented strategies are necessary to deal with this ongoing problem [3]. It has been recognized that several factors, including maternal traits and child and sociodemographic features, affect children's nutrition and health outcomes, including stunting [4].

Around 1.9 billion people globally were overweight, while 462 million were underweight, according to the WHO. Furthermore, it was reported that there were 47 million wasted U5 children, 14.3 million severely wasted children, 144 million stunted children, and 38.3 million overweight/obese children. Every year, 2.6 million children die from malnutrition and undernutrition worldwide, which is the cause of 45% of U5 deaths [5,6]. Poverty is not the only cause of malnutrition in Bangladesh; poor eating habits and a low level of nutritional knowledge also contribute to that. Child development still suffers from micronutrient deficiencies, particularly in the rural set-ups [7,8,9,10]. This is a multi-sectoral issue that requires collaboration among health, education, and food systems to address it.

Four hundred fifty thousand children suffered severe acute malnutrition, compared to over 2 million who suffered from mild acute malnutrition. The nutritional status of youngsters has steadily improved during the last few decades. In 2004, 43% of children were underweight, 41% in 2007, and 36% in 2011, whereas 51% of children were U5 stunted, 43% in 2007, and 41% in 2011. Similarly, in 2004, 17%, 16%, and 15% of U5 children were squandered. In 2014, these numbers fell to 14% overweight, 33% underweight, and 36% stunted [11]. To determine if a kid was malnourished, the height-for-age (stunted), weight-for-height (wasted), and weight-for-age (underweight) metrics were frequently employed. The children in most backward and deprived parts are in a constant state of nutritional backwardness [12,13,14]. The situation is exacerbated by social problems such as young motherhood, infancy without prenatal care, and poor availability of various, nutritious foods [15].

Malnutrition, including undernutrition, stunting, wasting, and overnutrition, is a significant global health issue in most regions of the world [16]. These disorders occur mainly because of inadequate intake of proteins, calories, and other essential nutrients that are necessary for proper growth and development [17]. Undernutrition, stunting, and wasting tend to be indicative of chronic and acute nutritional deprivation. In contrast, overnutrition occurs due to the intake of too many calories, hence, causing overweight and associated illness conditions [18]. If not appropriately addressed, malnutrition in children under five can potentially cause serious health problems, increasing the risk of developing various long-term health problems, such as diabetes, high blood pressure, stroke, behavioral disorders, and even death [19,20]. For the government (via the District Health Office) to promptly administer the required therapy, it is vital to identify the nutritional condition of children under five years old as soon as possible.

In the modern world, predictive techniques like machine learning are slowly replacing traditional methods as they are more accurate and flexible. In contrast to other conventional methods that rely on predetermined rules or manual data analysis, machine learning models are capable of learning data patterns themselves to make predictions. In machine learning, an ensemble technique is a group of models integrated to provide more accurate and reliable forecasts than those offered by any one model [21,22,23]. Ensemble methods combine the results of individual models, thus improving the stability of a result and its accuracy [24]. In the meantime, Explainable AI (XAI) is also a new field that aims to establish both transparent and interpretable models [25]. XAI tries to understand how the features of the input affect the model's decision to achieve a balance among performance, efficiency, and understandability.

According to previous studies, Malnutrition in children under five, especially in low-resource settings like Bangladesh, is driven by poverty, food insecurity, poor maternal health, inadequate sanitation, and limited healthcare access. Traditional assessment methods using anthropometric indicators (WAZ, HAZ, WHZ, MUAC) are effective but logistically challenging and not scalable in rural areas [26, 27]. Various machine learning models—such as Random Forest, SVM, XGBoost, KNN, logistic regression, CNN, and ANN—have been widely applied to predict malnutrition among children under five. In Bangladesh, studies using BDHS 2014 data showed that Random Forest and logistic regression achieved strong performance in classifying stunting, wasting, and underweight [30, 46, 53, 56]. Kar and Patel et al. found Random Forest and logistic regression to be top performers among Asian children aged 1–5 [32, 56]. In African countries like Ethiopia, Rwanda, and Zambia, ML models such as Random Forest, XGBoost, and neural networks effectively identified key predictors like maternal education, household wealth, and rural residence (31, 37, 50, 55). Similarly, studies from Pakistan and India demonstrated that SVM, decision trees, and ensemble methods achieved high accuracy by focusing on socioeconomic and demographic variables [40, 47, 48, 49].

Indonesian studies used Random Forest, SVM, and ensemble models to classify nutritional status based on BMI, age, and weight with excellent predictive results [34, 35]. Deep learning approaches, like CNN and ANN, were used for image-based or structured data detection, achieving superior performance in automated classification of malnutrition indicators [29, 43, 44].

Other studies explored hybrid methods combining clustering, logistic regression, and explainable AI tools such as SHAP and LIME for improved transparency in healthcare decision-making [41, 45, 51]. The study by Shahriar et al. and Talukder et al. verified the strength of ANN and RF models in the Bangladesh setting [43, 53]. Meanwhile, the meta-analysis by Rao et al. also highlighted the medium and high predictive effectiveness of ML that is consistent across research [55]. Ahmad and Rahmani in Afghanistan and Melese and Belay in Ethiopia used classification models such as Naive Bayes and xgbTree to determine socio-demographic risk factors of undernutrition [39, 42]. Asad and Zouq in Pakistan and a study by Lawrence et al. in Tanzania further confirmed the strength of ML models on high-risk areas [40, 47].

Previous works of Das et al. and Pena et al. were the first to reveal the principal connection between malnutrition, poverty, and maternal care, which are currently measurable by ML models [52, 54]. Lastly, comparative literature and other global reviews are highlighting the growing attention ML is receiving in the arena of public health nutrition and can facilitate early intervention [38, 55, 56].

Therefore, this study seeks to respond to the following research questions, considering the study's aims and objectives:

- To create a predictive model that uses anthropometric data to identify stunting, wasting, underweight, and overweight in children under five.
- To improve prediction accuracy, use an ensemble model that combines many machine learning techniques.
- To evaluate the model performance and make a comparison with the existing malnutrition detecting methods.
- The development of a practical framework that would allow the deployment of the model in healthcare facilities easily and efficiently to screen malnutrition.
- To validate the model with a real dataset and measure its applicability for use in the field of public health.
- To incorporate AI explainability techniques (e.g., SHAP, LIME) to interpret the model's decision-making process.

This study investigates multiple predictive modeling techniques—Logistic Regression, Random Forest, Decision Tree, Support Vector Machine, Multilayer Perceptron—and a novel stacked ensemble model for pediatric malnutrition classification. Each method is described with its corresponding optimization strategy, and models are trained and evaluated on preprocessed datasets partitioned into training and test subsets. Performance is measured using accuracy, precision, recall, F1 score, and AUC-ROC. The proposed work develops an ensemble model leveraging anthropometric data, validates it on real-world datasets, compares its performance with established approaches, integrates explainability tools (SHAP, LIME), and delivers a scalable, user-friendly framework for healthcare deployment.

2. Design Methodology

This research is conducted following a defined set of steps, and those steps are represented in a workflow diagram shown in Figure 1.

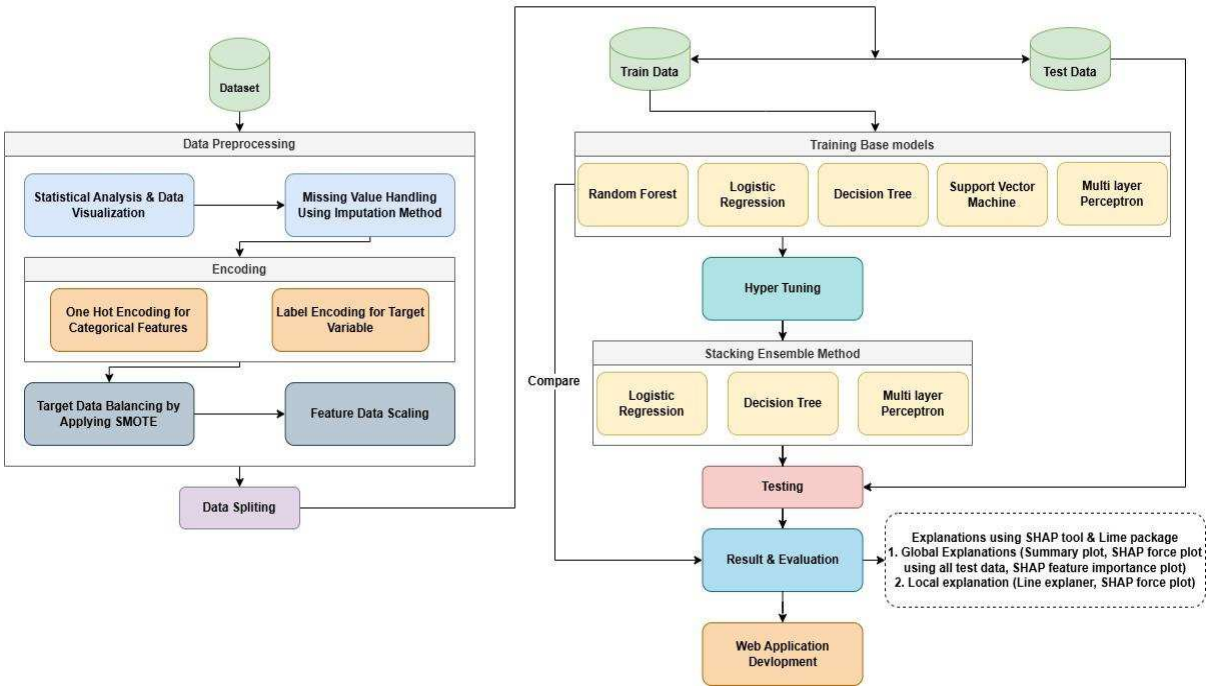


Figure 1. Block diagram of Methodology

2.1 Data Collection

The dataset was prepared to predict malnutrition in children aged 1 to 5, considering the socio-economic and environmental contexts of Noakhali and Lakshmipur in southern Bangladesh. These regions, with diverse urban and rural populations, are ideal for studying childhood malnutrition. The data was collected in person in the mentioned regions explicitly for this research, and has never been used elsewhere, ensuring its novelty. The collection process was carefully planned for accuracy, reliability, and ethical standards.

2.1.1 Dataset Description

Table 1 also provides a detailed description of the features of the exam: the range of values, data types, and descriptions. It lists 12 features, including weight, height, MUAC, and Z-scores (WAZ, HAZ, WHZ), as well as identifiers like gender, region, and ID. Additionally, the descriptive statistics in Table 2 offer information on various measures such as variance, standard deviation, and mean, which reveal the distribution and variability of the data. Some key characteristics in the dataset include MONTH, WEIGHT, HEIGHT, MUAC, WAZ, HAZ, and WHZ. For example, the feature MONTH has a mean of 32.87 and a standard deviation of 16.15, showing significant variability with values ranging from 6.47 to 59.96. On average, WEIGHT is 11.21 and HEIGHT is 83.72, while MUAC has a mean of 57 and a standard deviation of 11.27, indicating that these features vary around different values. The dataset also displays skewness along with minimum and maximum values for the features. Furthermore, the dataset contains some missing values in certain features, which were handled during the data pre-processing stage.

Table 1: Dataset Description

Feature	Value range	Data Type	Description
Area	0,1	Categorical	Geographical location
ID	1– 465	Numerical	Unique identifier for each record

SEX	0,1	Categorical	Gender of the individual (m/f)
BOD	2018 – 2023	Numerical	Birth year of the individual
MONTH	6.47 – 59.96	Numerical	Month of data collection
WEIGHT	4.0 – 21.0	Numerical	Weight of the individual (kg)
HEIGHT	50.0 – 115.0	Numerical	Height of the individual (cm)
MUAC	10.0 – 21.0	Numerical	Mid-Upper Arm Circumference (cm)
WAZ	-5.492 – 4.78	Numerical	Weight-for-Age Z-score
HAZ	-5.968 – 5.555	Numerical	Height-for-Age Z-score
WHZ	-4.963 – 4.997	Numerical	Weight-for-Height Z-score
Result	0.0 – 4.0	Categorical	Nutritional status (Normal, Overweight, Stunted, Underweight, Wasted)

Table 2: Statistical value of the dataset

Attribute	Distinct	Mean	Min	Max	Std	Var	Skew
BOD	12	nan	2018.0	2023.0	451.59	203942.08	-3.96
MONTH	375	32.87	6.5	59.96	16.14	260.69	-0.039
WEIGHT	29	11.21	4.0	21.0	2.95	8.75	0.43
HEIGHT	71	83.71	58.0	115.0	11.27	127.05	0.017
MUAC	57	14.24	10.0	21.0	1.35	1.82	0.39
WAZ	455	-1.42	5.4	4.7	1.99	3.99	0.45
HAZ	452	-2.011	5.968	5.555	2.9	8.41	0.76
WHZ	354	0.29	4.96	4.99	2.07	4.301	0.0023

2.1.2 Correlation Matrix

Figure 2 shows the correlation heatmaps, which show the connections between features using a color-coded matrix, where deeper shades represent stronger correlations. A strong positive correlation is observed between WEIGHT and HEIGHT, and MUAC also correlates well with WEIGHT, WAZ, and Result_Normal. Negative correlations are notable between Result_Stunted and key growth indicators like HAZ, WAZ, and WHZ, indicating that stunted children have low nutritional z-scores. Perfect negative correlations are also seen between binary variables such as SEX_f and SEX_m, and Area_Lakshmipur and Area_Noakhali. Overall, the heatmap helps identify influential features for further analysis and model development.

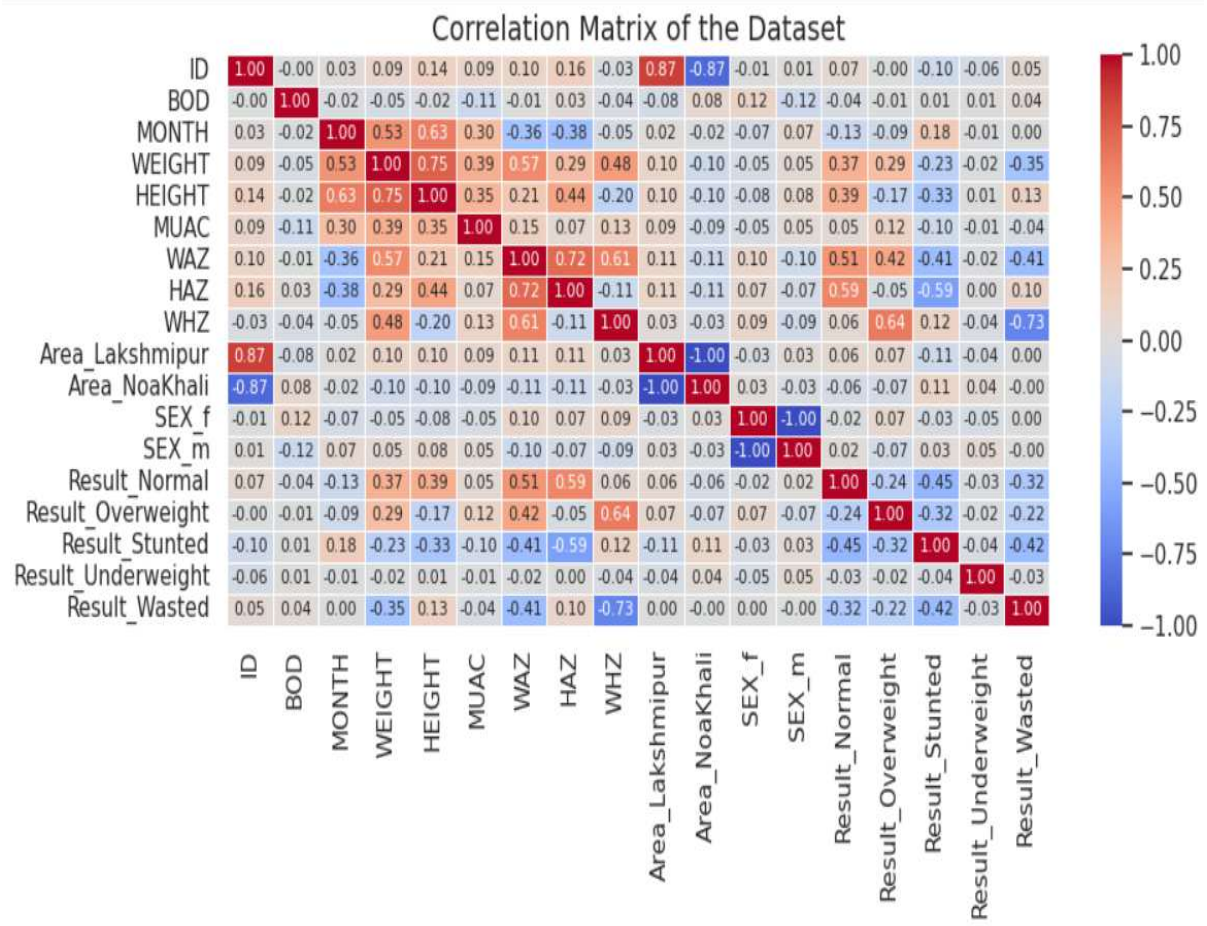


Figure 2. Correlation matrix of the dataset

2.2 Data Preprocessing

Preprocessing is a crucial step in preparing raw data to train machine learning (ML) models. It makes the information clean, structured, and transformed in a way that enables the model to perform the best and generalize more. In the present experiment, several preprocessing steps were used to guarantee the quality and applicability of a dataset in predictive modeling. Such preprocessing steps involved handling missing data, categorical variable encoding, feature augmentation, target data balancing, and feature scaling.

2.2.1 Missing Data Handling

One of the essential elements of preprocessing information is handling missing values. The Mean imputation would be preferred over the others since the flow of the missing values in our data conformed to the Missing Completely at Random (MCAR) pattern and is simple and effective. The imputation formula is given mathematically as:

$$X_{imputed} = \frac{1}{n}\sum X_i$$

Where $X_{imputed}$ represents the imputed value, X_i are the observed values, and n is the number of non-missing values for a particular feature.

2.2.2 Data Encoding

Two encoding strategies, One-Hot and Label, were applied. One-Hot encoding transformed categorical variables "SEX" and "Area" into binary columns indicating presence, shown in

Table 3. The target variable "result" (nutritional status) was encoded using Label Encoding, assigning each class a unique integer, as in Table 4.

Table 3: Sample of One-Hot Encoding

SEX - f	SEX - m	Area - Lakshmipur	Area - NoaKhali
0	1	1	0

Table 4: Label Encoding of Target Variable

Nutritional Status	Encoded Value
Normal	0
Overweight	1
Stunted	2
Underweight	3
Wasted	4

2.3 Data Balancing

Class imbalance in the target variable can lead to biased model predictions, particularly when the dataset contains underrepresented classes. The target variable of our dataset has 34.88%, 23.79%, 21.57%, 13.51%, and 6.25% for the courses of 'Stunted', 'Normal', 'Overweight', 'Wasted', and 'Underweight'. To mitigate this imbalance, the Synthetic Minority Oversampling Technique (SMOTE) was used to balance the classes in the target variable, 'Result'. SMOTE generates synthetic examples by interpolating between the chosen instance and its closest neighbors after choosing instances from the minority class. Figures 3 and 4 show the imbalance and balance of the target variable.

2.4 Feature Data Scaling

Feature scaling is also necessary when the features of the dataset are not of the same range or level, as a feature may overshadow the other features during model training. To normalize the features, the Standard Scale of scikit-learn was utilized. The data is normalized by subtracting the mean from the data and dividing the result by the standard deviation. This guarantees a mean of 0 and a standard deviation of 1 for every feature. The standardization formula is:

$$X_{scaled} = \frac{X - \mu}{\sigma}$$

Where μ is the mean of the feature, and σ is the standard deviation. This change ensures each feature gives equal input to the model, the key consideration in distance-based algorithms such as support vector machine and the k-nearest neighbors.

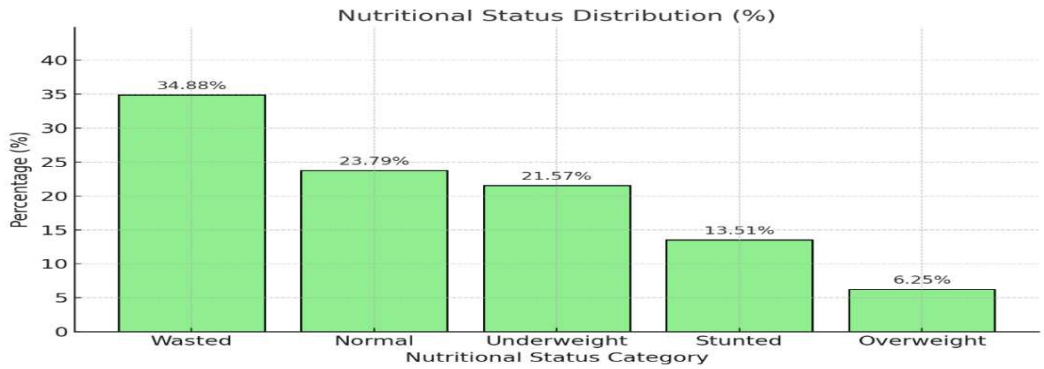


Figure 3. Before balancing the target variable

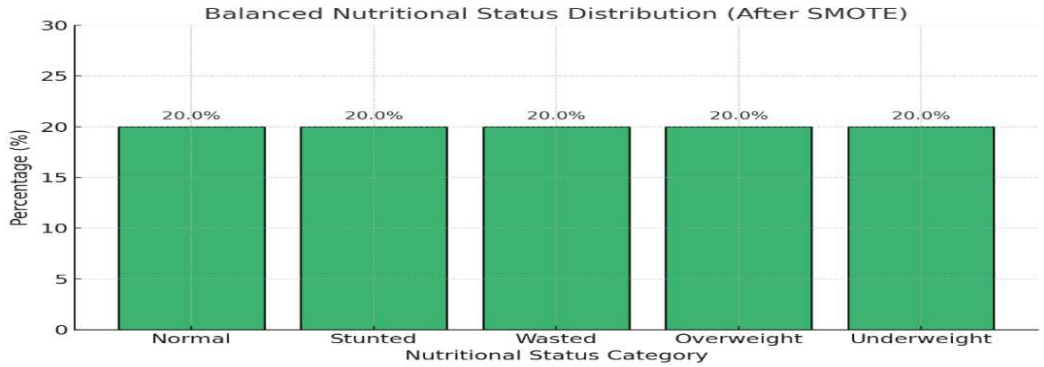


Figure 4. After balancing the target variable

2.5 Data Splitting

To test the performance of the model, the data was divided into training and testing. The split between a training and testing set was developed at 80% and 20% points using the train_test_split on the scikit-learn package. This checks to see that the model is trained using the right size of the data set, but leaves a different, and unseen part of the data set to analyze performance.

3. Machine Learning Models

After splitting the data, some traditional supervised machine learning models are employed to train the training dataset. A brief description of the employed ML models is given in the following sections.

3.1 Logistic Regression

Logistic Regression is a linear model typically used for binary classification tasks [57,58]. This algorithm determines the data point class probability through a logistic transformation process of the weighted summation of input features. The investigation used logistic regression to make predictions about malnutrition status through the analysis of continuous and categorical traits. The algorithm provides a straightforward solution delivering efficient performance with clear interpretability, so it functions as a reliable baseline. This model offers exceptional results in cases where the connection between features and the target variable follows a linear pattern.

3.2 Random Forest Classifier

Random Forest functions as an ensemble learning approach to build its base using decision trees but delivers more accurate results, together with reduced overfitting by developing

numerous decision trees from random data subsets, followed by blending their predictions [59]. Random Forest Classifier establishes predictions by running multiple decision trees to learn feature interplay patterns and detect data-set non-linearity [60, 61]. Random Forest enables users to deal with complex data structures while allowing them to study which features are most important. It performs a complete analysis of datasets across all dimension levels to present detailed information about key features regardless of feature type.

3.3 Decision Tree Classifier

Decision Tree Classifier is a non-ensemble and a rule-based model that recursively partitions the dataset according to the values of the features and results in a tree representation where each leaf node gets its label, which is the class [62, 63]. In the study, this model was added thanks to its simple organization, high explainability, and the possibility of discovering non-linear patterns in the data. In the present study, the Decision Trees were especially appreciated for their transparency, which provides clear visual decision-making routes that can be applicable in clinical or policy-based settings.

3.4 Support Vector Machine

Support Vector Machine (SVM) exists as a supervised learning system. The optimization method chooses the hyperplane that produces the maximum possible space between different category groups. SVM manages three key components that comprise data mapping from the kernel function, combined with the penalty parameter C for misclassification severity determination, and the gamma parameter to set legacy values. It has good modelling properties on health-oriented data because of its robustness in high-dimensional feature spaces. Also, SVM has good generalization capacity that reduces the chances of overfitting, which is essential for practical prediction tasks, such as child malnutrition detection [64, 65].

3.5 Multi-Layer Perceptron

Multi-Layer Perceptron (MLP) is a feedforward neural network designed to model complex, non-linear data patterns [66]. It features a non-linear input layer, one or more hidden layers with activation functions, and an output layer. In this study, MLP was used to classify malnutrition outcomes based on anthropometric and demographic data. Its architecture enables learning complex feature interactions that simpler linear models may miss. MLPs perform well when feature separation is challenging, and they can learn and generalize effectively with sufficient data, even amid noise. The MLP contributed to the stacking ensemble's deeper learning, improving overall performance.

3.6 Stacking Ensemble Method

The stacking ensemble method was adopted in this research to enhance overall classification performance by leveraging the predictive strengths of multiple base models. Unlike other ensemble strategies like bagging or boosting, where a set of different classifiers is trained together, in stacking, several different classifiers are individually trained (base learners). Then their predictions are combined based on a second-level model, the meta-learner [68]. In this study, base learners included models such as Logistic Regression, Decision Tree, and Multi-Layer Perceptron (MLP). At the same time, the meta-learner was implemented using Logistic Regression due to its simplicity and interpretability. The stacking approach combined diverse

base models (e.g., Decision Trees, MLP) to capture varied patterns, with a Logistic Regression meta-model trained on their outputs to optimize final predictions. This ensemble strategy improved generalization, reduced overfitting, and handled complex or imbalanced data effectively. The process of stacking classifiers in our methodology is shown in Figure 5.

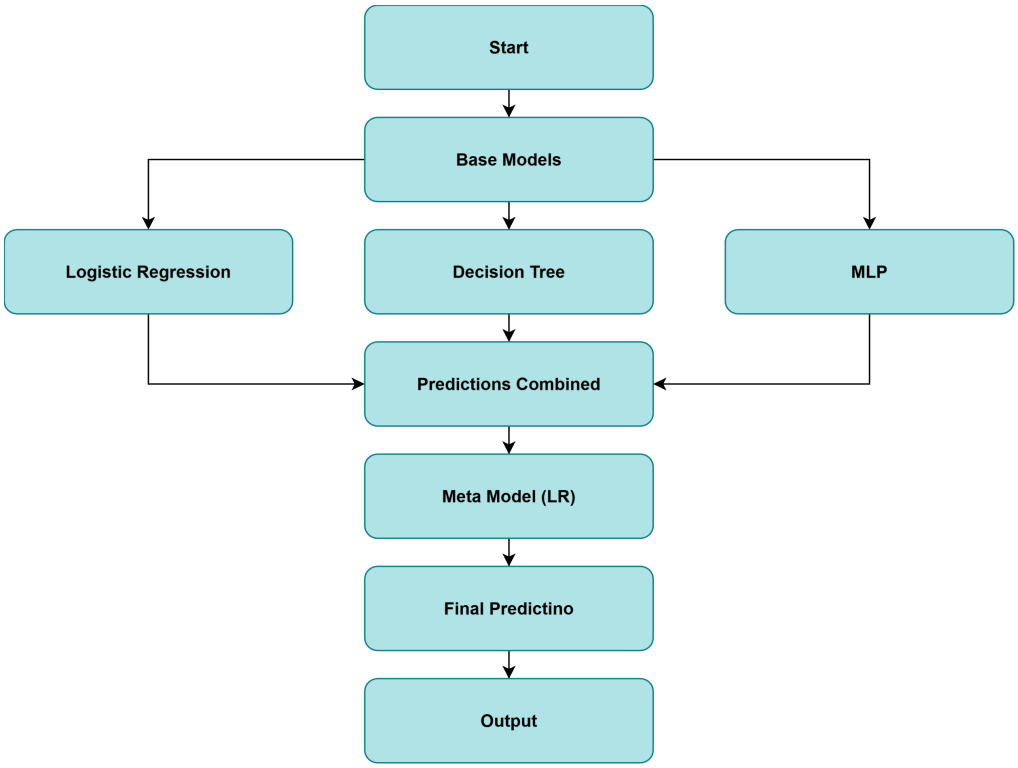


Figure 5. Stacking ensemble flowchart

Algorithm 1: Proposed Stacking Ensemble Model

Input: • *Training dataset X_train_scaled, target labels Y_train_resampled* • *Testing dataset X_test_scaled, ground truth Y_test* • *Base learners: Logistic Regression (LR), Decision Tree (DT), Multi-Layer Perceptron (MLP)* • *Meta learner: Logistic Regression (LR)*
Output: • *Final prediction results y_pred_stack and evaluation metrics*
Steps: 1. *Initialize base learners B = {Logistic Regression, Decision Tree, MLP}.* 2. *Define meta-learner M = Logistic Regression.* 3. *Construct stacking model using 5-fold cross-validation: StackModel = StackingClassifier(B, M, cv=5).* 4. *Train the stacking model using the training set: StackModel.fit(X_train_scaled, Y_train_resampled).* 5. *Predict on the testing set: y_pred_stack = StackModel.predict(X_test_scaled).*

6. *Evaluate model performance using Accuracy, Precision (macro-average), Recall (macro-average), F1 Score (macro-average), Confusion Matrix, and Classification Report.*
7. *Display the confusion matrix with class labels: Normal, Overweight, Stunted, Underweight, Wasted.*
8. *Return y_pred_stack as the final prediction result.*

Figure 6 shows the stacking ensemble model used in this study. It combines base classifiers—Multi-Layer Perceptron (MLP), Decision Tree (DT), and Logistic Regression (LR)—each trained separately. Their predictions feed into a Logistic Regression meta-classifier that combines outputs for the final prediction. This layered approach aims to boost accuracy, reduce bias, and leverage each model's strengths.

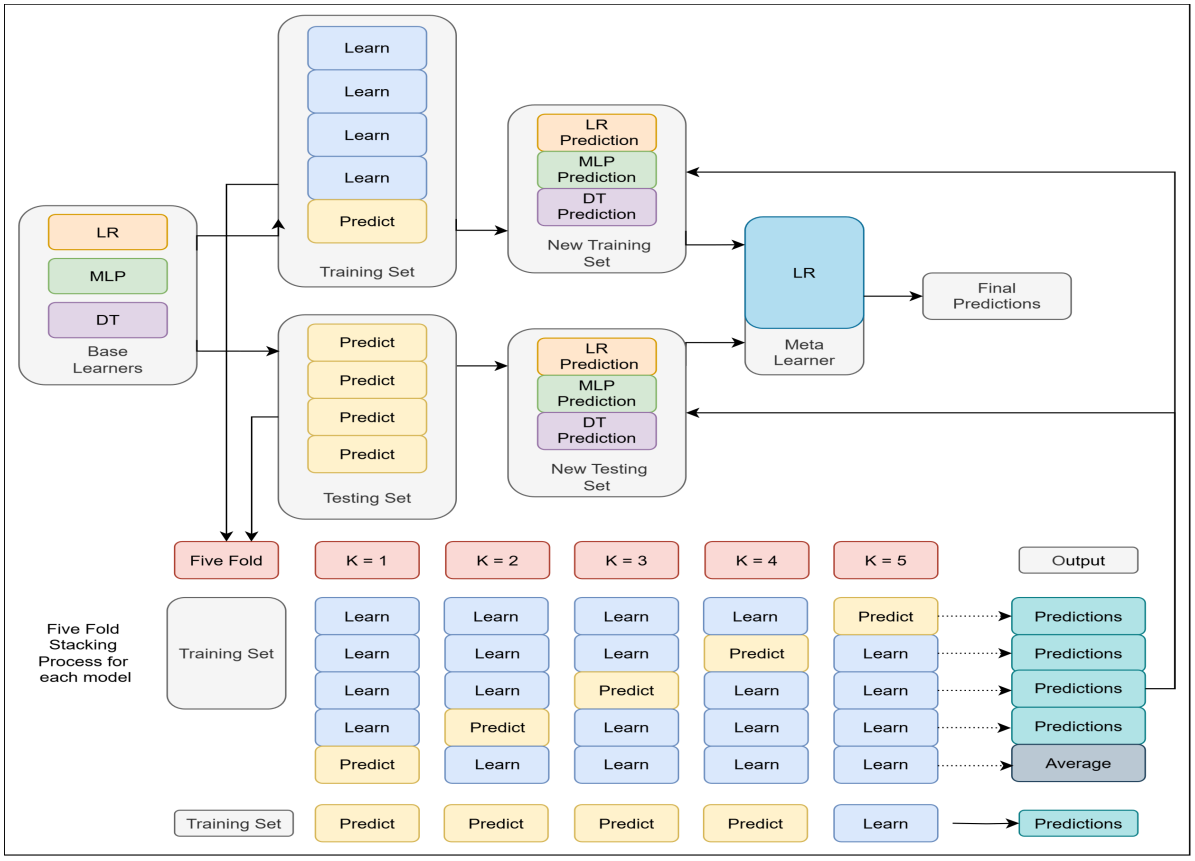


Figure 6. Architecture of stacking ensemble learning

3.7 Hyperparameter Tuning

In machine learning, hyperparameters are the external settings of a model that cannot usually be learned directly out of the data but have a significant effect on the performance of a model [69]. To determine the best combination of hyperparameters of each of the classifiers utilized in this study, "GridSearchCV" and "RandomSearchCV" were used instead of using the default parameters. In this work, a 5-fold cross-validation was used; hence, models are not over-fitted on a specific training fold.

3.8 Performance Matrices

It is an N × N matrix called the "Confusion Matrix" that evaluates performance measures like accuracy, precision, and recall by comparing predicted and actual results. For a binary classifier, it has four sections: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). Models are analyzed using evaluation metrics shown in Table 6. Overall performance was gauged via the ROC curve, which compares True Positive and False Positive Rates. Multi-class analysis used one-vs-rest. Model performance was measured by the Area Under the Curve (AUC), with higher AUC indicating better performance as classes are farther apart. The stacking ensemble achieved the highest AUC, indicating strong generalization ability.

Table 5: Brief Description of Evaluation Criteria

Metrics	Definition	Equation
Accuracy	It calculates the ratio of connection records that were correctly identified to all test records. (Accuracy ϵ [0,1]).	$\frac{TP + TN}{TP + TN + FP + FN}$
Precision	It determines the percentage of all detected assault connection records that are accurately detected. (Accuracy ϵ [0,1]).	$\frac{TP}{TP + Fp}$
Recall	The percentage of malnutrition connection records that are accurately categorized as all of the Assault connection records is determined by this. (Remember ϵ [0,1]).	$\frac{TP}{TP + FN}$
F1-Score	It is the harmonic mean of precision and recall. (F1-Score ϵ [0,1]).	$2\times (\frac{Precision \times Recall}{Precision + Recall})$

3.9 Explainable AI

This study used SHAP and LIME for transparency in predictive modeling. SHAP explains model outputs by showing feature contributions [70], helping justify high-risk predictions. LIME, an explanation tool, creates local surrogate models to clarify individual predictions [71], making complex ensemble models understandable. It aids in explaining errors and marginal cases, complementing SHAP and enhancing interpretability.

4. Result Analysis

4.1 Exploratory Data Analysis

Exploratory Data Analysis (EDA) is simply the way of analyzing and assessing data sets to identify patterns, make essential insights, and demonstrate how different variables relate to one another. In this study, EDA is used to investigate the characteristics of the dataset, providing a foundation for further analysis. The primary use of EDA is to recognize the structure that the data belongs to and learn how various variables act.

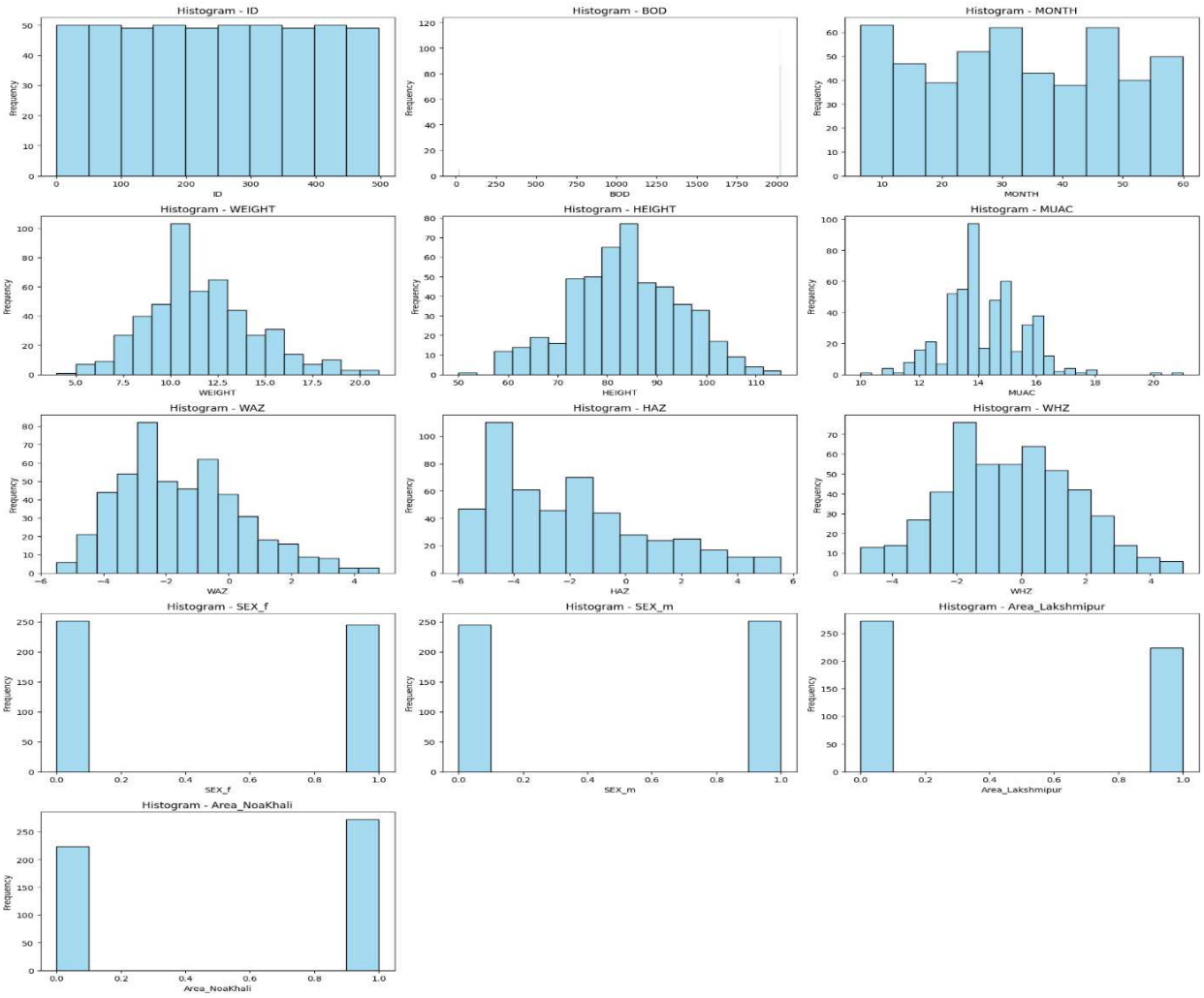


Figure 7. Histogram of features

4.1.1 Histogram Analysis

The histogram in Figure 7 shows the frequency of the numerical features of the presented dataset. The range of values of each feature is indicated along the x-axis, and the frequency against each of the features is shown along the y-axis. This figure, therefore, indicates how the significant variables were distributed. The measure of age in months is not very diverse, ranging from 0 to 60 months, while weight (10-12.5 kg) is correct, and the height (80-90 cm) is likely to be normally distributed. MUAC (mid-upper arm circumference) has more of the same right-skewed distribution with much concentration of the observations between 14 and 15 cm, which shows variability within the risk of acute malnutrition. In case of anthropometric measures, the HAZ and WAZ tests are skewed downwards, meaning that a large percentage of children were below zero, which was interpreted as a significant prevalence of underweight and stunted children. By comparison, however, the WHZ scores are more symmetrical and indicate moderate wasting. In terms of area and sex, the sample is very similar as it is skewed across both genders and the geographical regions.

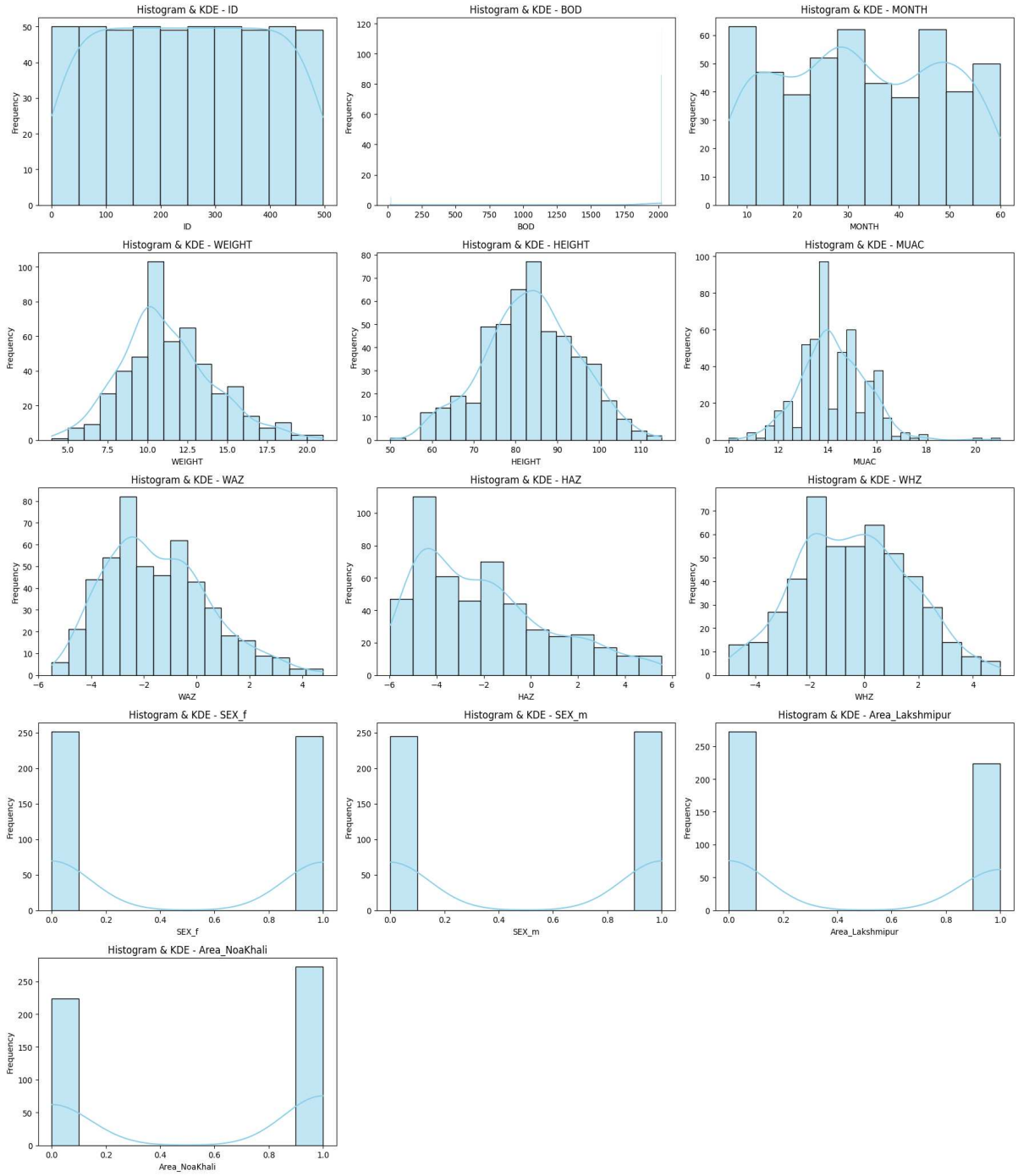


Figure 8. KDE plot of features

4.1.2 KDE Plot Analysis

Kernel Density Estimation (KDE) is a non-parametric method of estimating the probability density function of a continuous variable. Individual observations are smoothed with a bell-shaped kernel to create a smooth, differentiable approximation, often better at capturing multimodal structures than parametric methods. A KDE plot visually depicts the distribution of numerical variables, as shown in Figure 8. Overlaying KDE on histograms reveals key information, such as distribution shapes. The MUAC shows a slightly skewed distribution with a sharp peak, indicating most children have a narrow mid-upper arm circumference range. WAZ, HAZ, and WHZ are likely left-skewed, reflecting prevalent undernutrition.

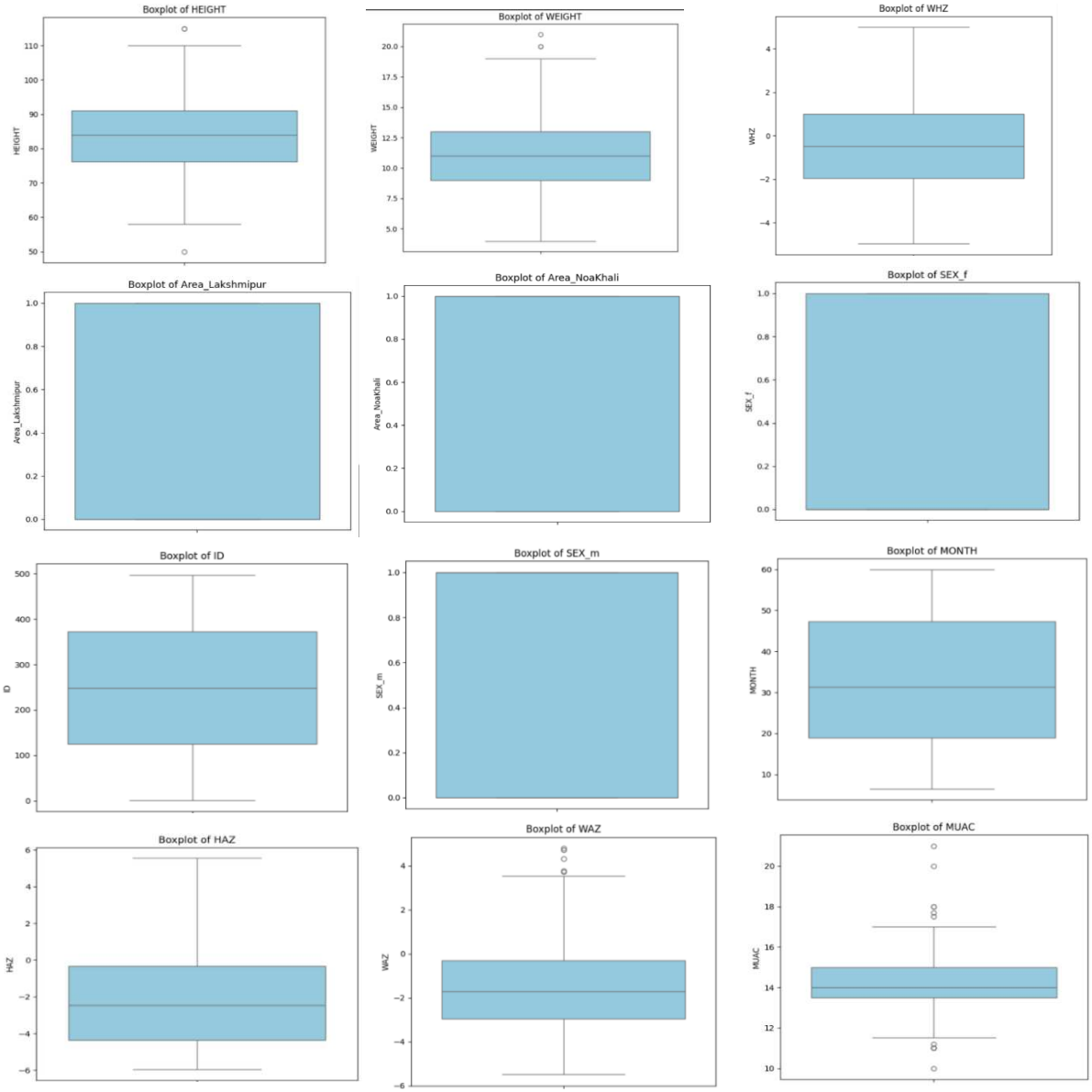


Figure 9. Boxplot of features

4.1.3 Box Plot Analysis

Box plots visualize the distribution, central tendency, and variability of anthropometric and demographic variables. Each box shows the interquartile range (IQR), with a median line, and whiskers extend to 1.5×IQR. Outliers appear as dots beyond the whiskers. This provides a view of data symmetry, spread, and anomalies. Key variables are shown in Figure 9. HAZ exhibits slight left skewness, indicating stunting, while WAZ shows moderate variability with outliers, suggesting dispersion or overnutrition. MUAC indicates high and low outliers, highlighting acute malnutrition. Weight and Height distributions are symmetrical; WHZ appears balanced. The Month variable, ranging from about 6 to 60 months, covers a wide age range. Sex and Area variables form solid vertical blocks due to only two categories, unlike potential bar or pie charts.

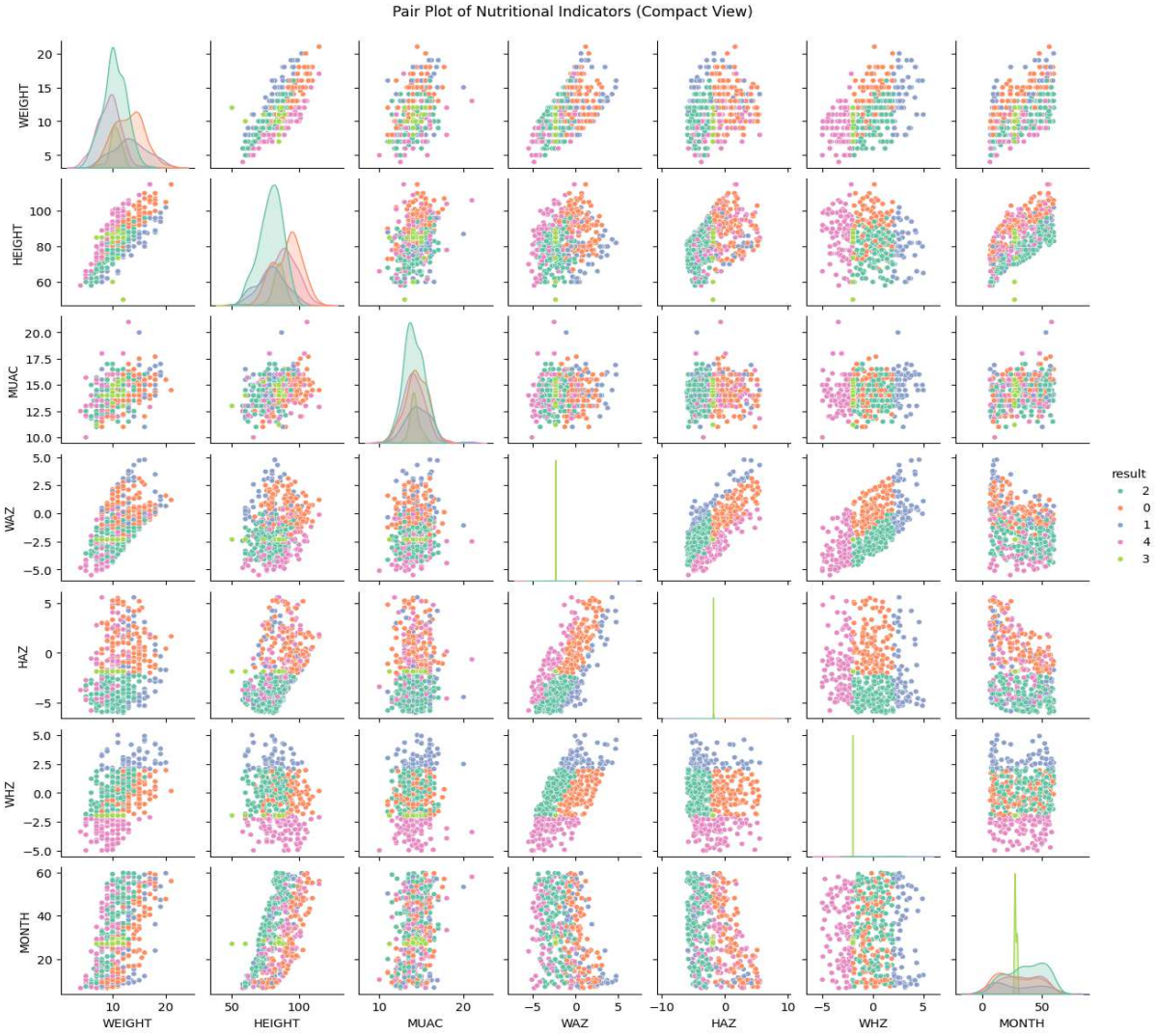


Figure 10. Pairwise relationship of multiple variables in the dataset.

4.1.4 Pair Plot Analysis

The pair plot visualizes relationships between numerical variables, showing correlations, clustering, and patterns within the dataset. Figure 10 displays a grid with kernels on the diagonals for distributions and scatter plots in other cells for comparisons. Colors represent five malnutrition severity categories, helping to identify patterns at different nutritional levels. The plot maps variables like WEIGHT, HEIGHT, MUAC, WAZ, HAZ, WHZ, and MONTH. Notably, there is a strong positive correlation between WEIGHT and HEIGHT, and between WEIGHT and MUAC, highlighting anthropometric interdependence. Moreover, the results of the KDE two-dimensional plots of WHZ, HAZ, and WAZ reveal typical skewness, a result already recorded in the analysis. In some of the scatter plots, a vertical or horizontal straight-line construction appears, which implies a lack of variation or the existence of outliers, and this should be factored in during the further investigation stages. The pair plot, in total, highlights the non-linear and complicated form of relations between these growth indicators and supports the idea that more complex statistical models are still needed to estimate the results of malnutrition precisely.

4.2 Machine Learning Model's Performance Analysis

4.2.1 Logistic Regression

The Logistic Regression model's performance was evaluated on training and testing datasets, summarized in Tables 6 and 7. It showed stability across nutritional categories, with high accuracy—98.84% on training and 91.00% on testing—and robust metrics: Precision 93.75%, Recall 88.51%, and F1-Score 90.58% on testing. The confusion matrix (Figure 10) confirmed high accuracy, especially perfect in the Stunted category and near perfect in Wasted. Most misclassifications involved closely related categories like Normal, Underweight, and Overweight, suggesting a need for better feature separation. The ROC curve (Figure 12) indicated strong predictive power with AUC scores of 1.00 for Overweight and Stunted, 0.99 for Wasted, 0.98 for Normal, and 0.90 for Underweight. Overall, the model demonstrates high sensitivity, specificity, and reliability, suitable for real-world multiclass malnutrition prediction.

Table 6: Training and Testing Performance

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Training	98.84	98.84	98.84	98.84
Testing	91.00	93.75	88.51	90.58

Table 7: Classification Report (Test Set)

Class	Precision	Recall	F1-Score
Normal (0)	0.95	0.79	0.86
Overweight (1)	1.00	0.85	0.92
Stunted (2)	0.90	1.00	0.95
Underweight (3)	1.00	0.83	0.91
Wasted (4)	0.84	0.95	0.89

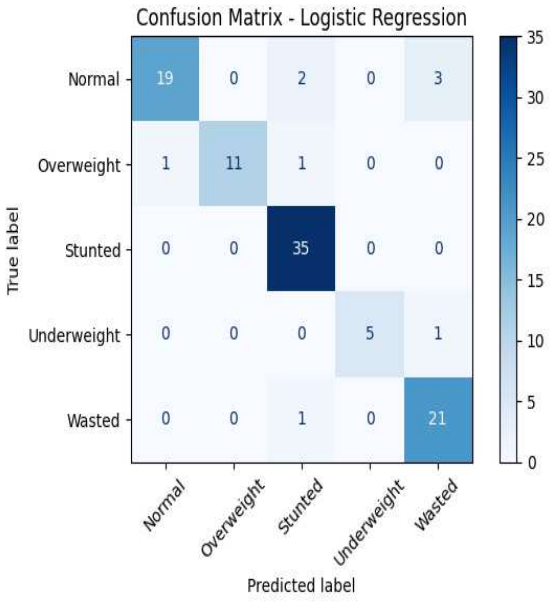


Figure 11. Confusion Matrix of Logistic Regression

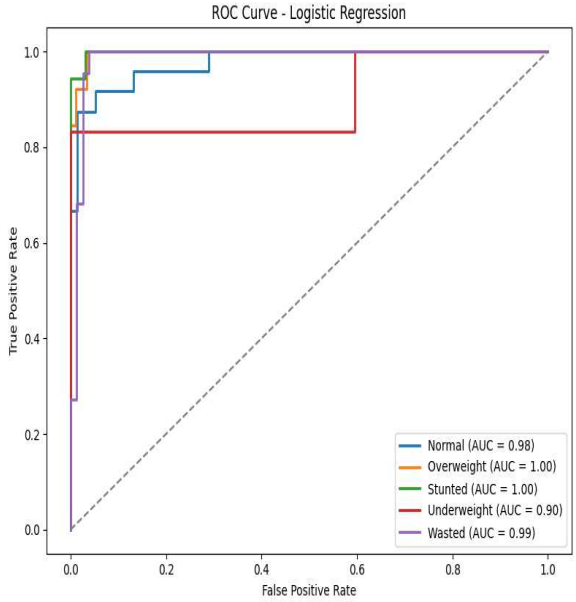


Figure 12. ROC Curve of Logistic Regression

4.2.2 Random Forest

The Random Forest model achieves a training accuracy of 98.41% and a test accuracy of 97.00% (Tables 8 and 9). Each class has high precision (~97%), recall (~97.87%), and F1-scores (~97.53%), indicating minimal overfitting and good generalization. Classes 3 and 4 reach perfect scores of 100%. The confusion matrix (Figure 13) shows the model is more effective than others, with only three misclassifications: two overestimations (Stunted as Normal) and one underestimation (Overweight as Stunted). These errors suggest infrequent class relationships. The matrix confirms high precision, enhancing credibility. The ROC curve (Figure 14) shows an AUC of 1.00 for Normal, Overweight, Underweight, and Wasted, and 0.99 for Stunted, demonstrating the model's accuracy in predicting malnutrition types.

Table 8: Training and Testing Performance

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Training	98.41	98.42	98.41	98.41
Testing	97.00	97.87	97.32	97.53

Table 9: Classification Report (Test Set)

Class	Precision	Recall	F1-Score
Normal (0)	0.92	1.00	0.96
Overweight (1)	1.00	0.92	0.96
Stunted (2)	0.97	0.94	0.96
Underweight (3)	1.00	1.00	1.00
Wasted (4)	1.00	1.00	1.00

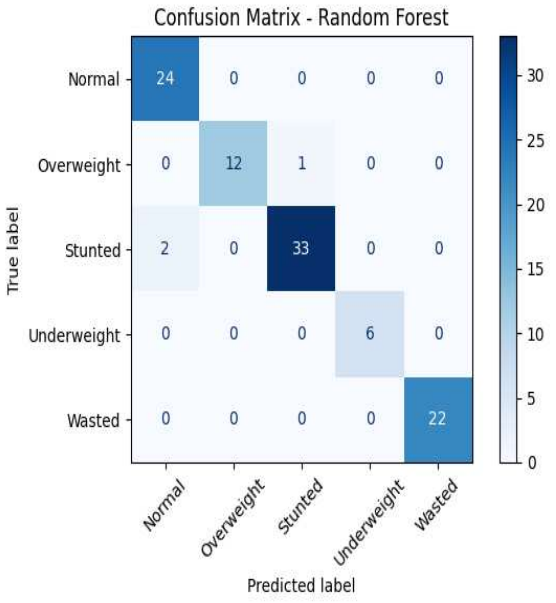


Figure 13. Confusion Matrix of Random Forest

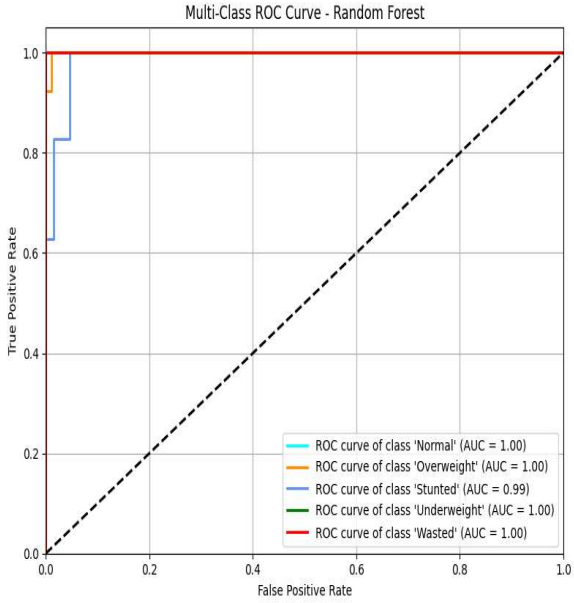


Figure 14. ROC Curve of Random Forest

4.2.3 Decision Tree

The decision tree was optimized using "RandomizedSearchCV", enhancing its predictive power. Tables 10 and 11 display the model's strong, interpretable performance. While accuracy is high across all classes, Wasted and Normal classes achieve a 93% correct classification rate, as confirmed by the confusion matrix in Figure 15. Most classes are accurately predicted, except the Stunted class, which misclassifies into Overweight four times. These results suggest that the model effectively classifies nutritional statuses with minimal overlap, supported by the ROC curve in Figure 16, where most scores exceed 0.90, and Wasted reaches 1.00. Overall, the Decision Tree demonstrates reliable, discriminative accuracy, offering a promising approach for nutritional health evaluation.

Table 10: Training and Testing Performance

Metric	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Training	95.65	95.65	95.65	95.65
Testing	93.00	93.00	93.00	93.00

Table 11: Classification Report (Test Set)

Class	Precision (%)	Recall (%)	F1-Score (%)
Normal (0)	1.00	0.96	0.98
Overweight (1)	0.71	0.92	0.80
Stunted (2)	0.94	0.89	0.91
Underweight (3)	1.00	0.83	0.91
Wasted (4)	1.00	1.00	1.00

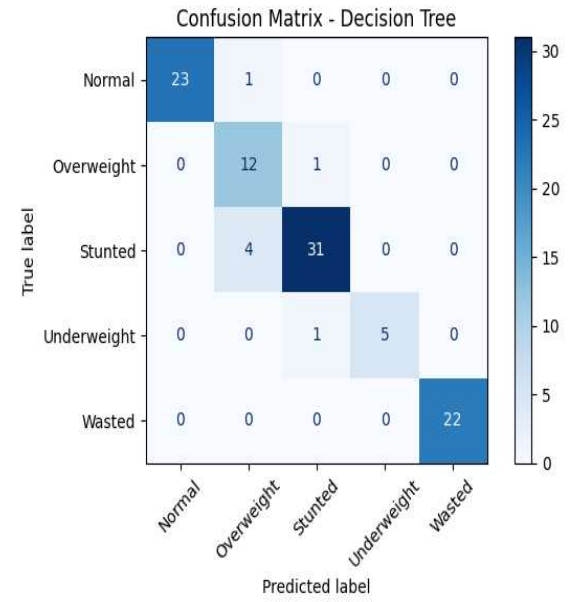


Figure 15. Confusion Matrix of Decision Tree

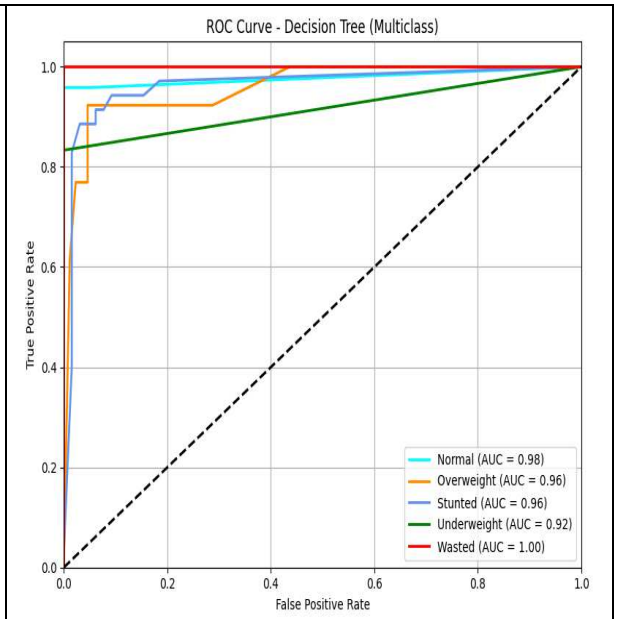


Figure 16. ROC Curve of Decision Tree

4.2.4 Support Vector Machine

Using an SVM model with a linear kernel and C=10 was very successful, as shown in Tables 12 and 13. The training and testing accuracies were 99.57% and 91%, indicating effective

learning with some bias. Class evaluation showed Class 1 had perfect precision, recall, and F1-score (1.00), while Classes 2 and 3 had strong F1-scores of 93% and 91%. Classes 0 and 4 had good precision but lower recall, indicating coverage issues. Figure 17 highlights the model's good performance, especially in the Overweight category, with all predictions accurate. Wasted and Stunted categories also showed good accuracy, with only three misclassifications in Normal and one Underweight predicted as wasted. The ROC curve in Figure 18 confirms the model's effectiveness, with excellent AUC values across all classes, showing strong sensitivity, specificity, and predictive performance (AUCs of 1.00 in Overweight, 0.99 in Normal, Stunted, Wasted, and Underweight).

Table 12: Training and Testing Performance

Dataset	**Accuracy**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Training	99.57	99.57	99.57	99.57
Testing	91.00	93.16	90.71	91.62

Table 13: Classification Report (Test Set)

Class	Precision	Recall	F1-Score
Normal (0)	0.91	0.83	0.87
Overweight (1)	1.00	1.00	1.00
Stunted (2)	0.94	0.91	0.93
Underweight (3)	1.00	0.83	0.91
Wasted (4)	0.81	0.95	0.88

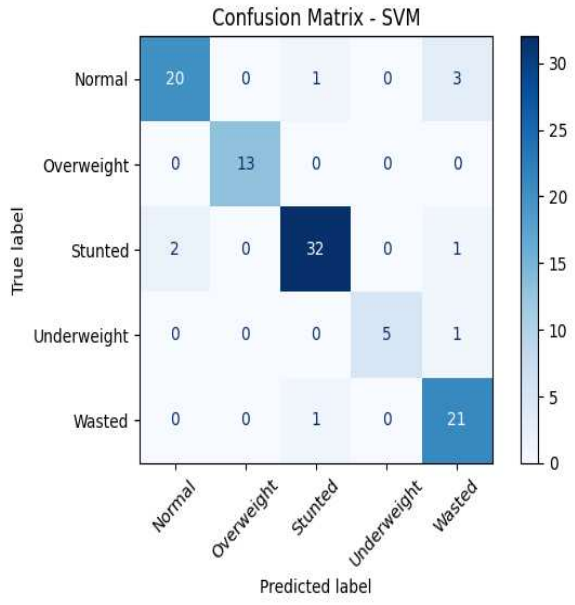


Figure 17. Confusion Matrix of SVM

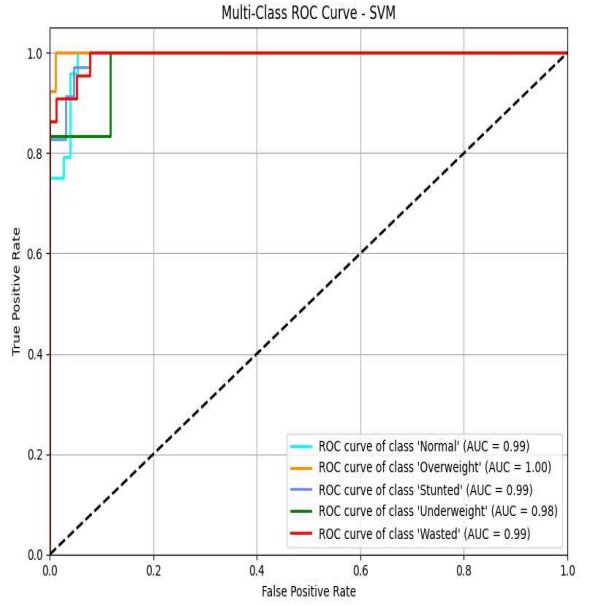


Figure 18. ROC Curve of SVM

4.2.5 Multi-layer Perceptron

MLP achieved a training accuracy of 98.26% and testing accuracy of 89.00%, with an F1-score of 89.07%, indicating good generalization and minimal overfitting. Its architecture captured complex data patterns, scoring well on Overweight, Stunted, and Underweight classes (F1 ≥

0.90%). Scores were slightly lower for Normal and Wasted due to class imbalance. The confusion matrix (Figure 19) showed 33 of 35 Stunted and 20 of 22 Wasted cases were correct, while the Normal group had 20 correct predictions. Overweight had 11 correct predictions, and Underweight was less accurate, with five correct and one error. ROC analysis (Figure 20) confirmed effectiveness, with AUC values of 0.99 for Overweight, Stunted, and Wasted, and 0.98 for Normal and Underweight. These results establish MLP as a strong, effective model for multi-class nutritional status classification.

Table 14: Training and Testing Performance

Set	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Training	98.26	98.26	98.26	98.26
Testing	89.00	92.20	87.00	89.07

Table 15: Classification Report (Test Set)

Class	Precision	Recall	F1-Score
Normal (0)	0.91	0.83	0.87
Overweight (1)	1.00	0.85	0.92
Stunted (2)	0.87	0.94	0.90
Underweight (3)	1.00	0.91	0.91
Wasted (4)	0.83	0.83	0.87

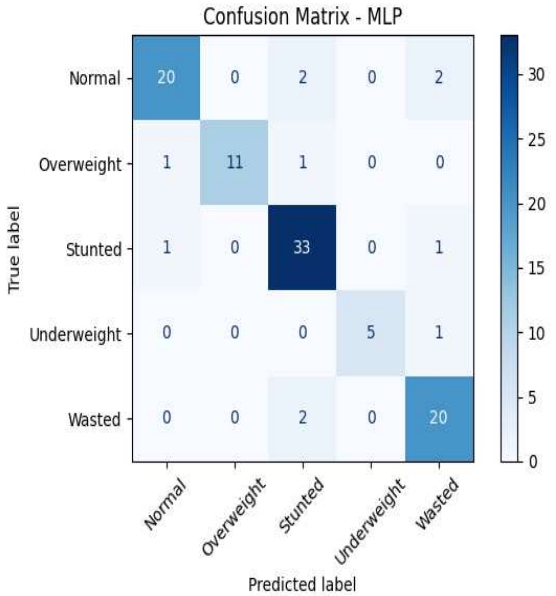


Figure 19. Confusion Matrix of MLP

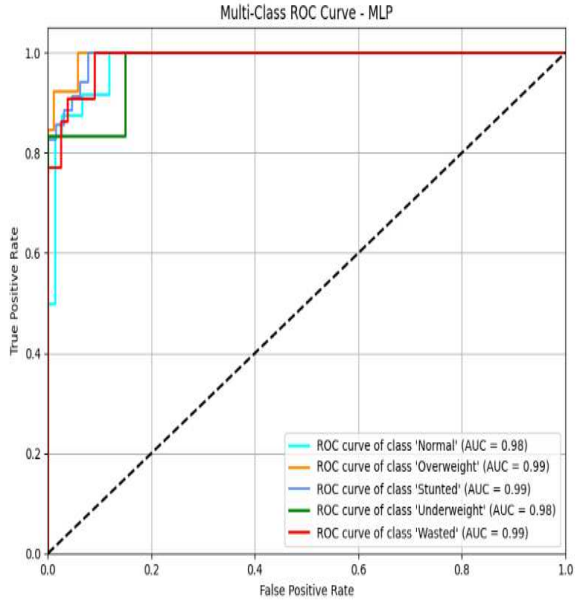


Figure 20. ROC Curve of MLP

4.2.6 Stacking Classifier

The Stacking Classifier, an ensemble learning approach, performed well overall and per class. Table 16 shows its performance before and after optimization. Initial accuracy was 98.00%, with precision 98.20%, recall 95.67%, and F1-score 95.77%, with some misclassifications. After hyperparameter tuning with "Optuna" and "RandomizedSearchCV," accuracy improved to 99.00%, precision 99.20%, recall 96.67%, and F1-score 97.77%, enhancing class balance

and stability. Chosen for its ability to capture diverse patterns, stacking boosted generalization, and robustness in multi-class nutritional prediction. Figure 21 compares training and testing accuracy of the ensemble, showing 99.18% during training and 99.00% during testing, indicating good learning without overfitting. The close scores suggest the model is reliable in predicting child malnutrition.

Table 16: Comparison of Stacking Classifier Performance Metrics

Metric	Pre-Optimization (%)	Post-Optimization (%)
Accuracy	98.00	99.00
Precision	98.20	99.20
Recall	95.67	96.67
F1-Score	95.77	97.77

Table 17: Classification Report - Stacking Classifier

Class	Precision (%)	Recall (%)	F1-Score (%)
Normal (0)	0.96	1.00	0.98
Overweight (1)	1.00	1.00	1.00
Stunted (2)	1.00	1.00	1.00
Underweight (3)	1.00	0.83	0.91
Wasted (4)	1.00	1.00	1.00

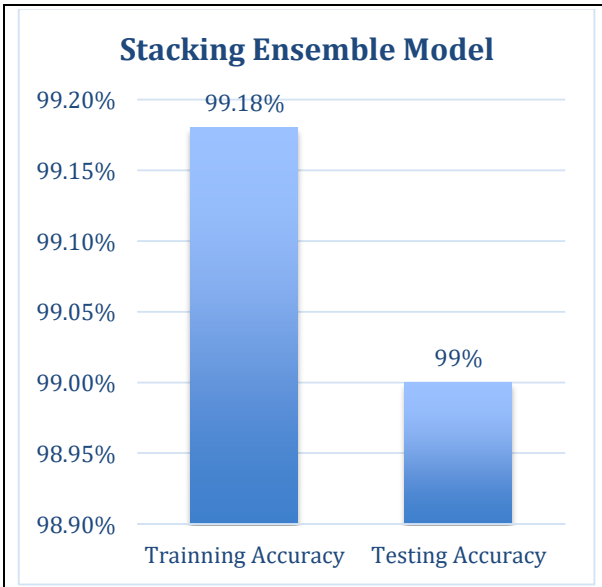


Figure 21. Training and Testing Accuracy of the Stacking Ensemble Model

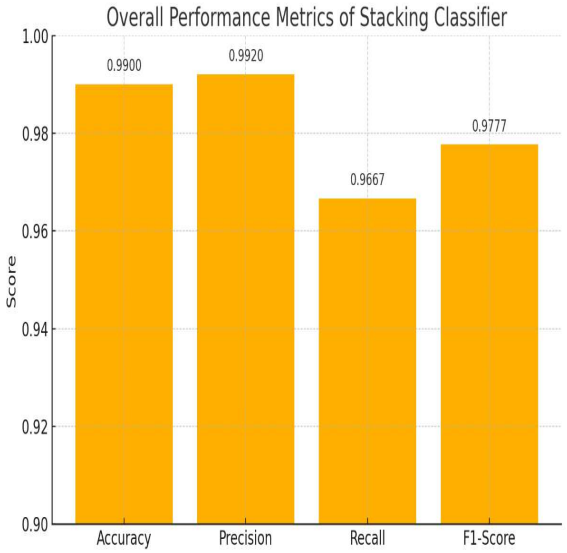


Figure 22. Performance Matrices of the Stacking Classifier

Table 17 shows high results, with the Overweight, Stunted, and Wasted classes reaching 100% precision, recall, and F1-score, indicating perfect detection without errors. The Normal class achieved a 98.00% F1-score, reflecting high accuracy. The Underweight class had 83.00%, with some cases missed, but perfect precision. Overall accuracy was 99.00%, showing stability across classes. The confusion matrix in Figure 23 shows the Stacking Classifier performed well

across five categories, with perfect classification for Overweight (13/13), Stunted (35/35), and Wasted (22/22). The Normal class had 24 correct out of 25, with 1 misclassified as Underweight. The Underweight class had 5 correct and 1 misclassified as Normal, with lower recall of 0.83%. ROC scores of 1.00, 0.99, 0.99, and 0.99 for Overweight, Normal, Stunted, and Wasted confirmed high effectiveness, and the Underweight class had an AUC of 0.98. These results demonstrate the model's strong discriminating power using the same nutritional variables.

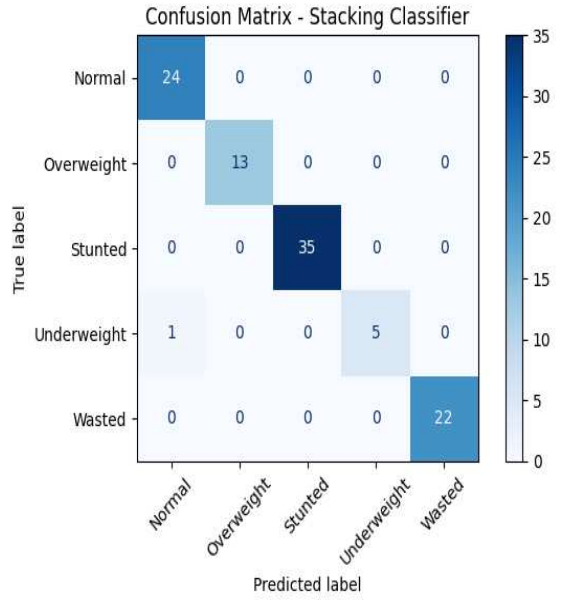


Figure 23. Confusion matrix of Stacking Classifier.

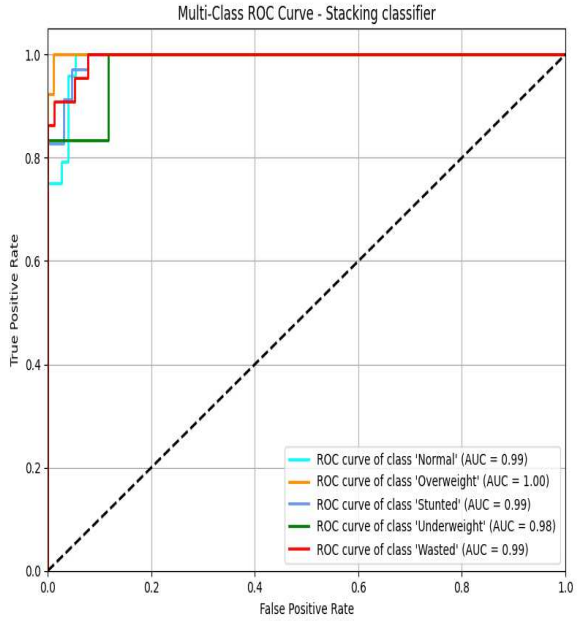


Figure 24. ROC curve of a stacking classifier

4.3 Comparison of All Models' Performance

The models in this study underwent hyperparameter tuning, with parameters in Table 18. Performance shown in Table 19 and Figure 25 revealed that the Stacking Classifier outperformed other models, achieving 99.00% accuracy, 99.20% precision, 96.67% recall, and a 97.77% F1-score, indicating superior generalization due to diverse base learners. Random Forest achieved 98.00% accuracy and 97.32% F1-score. The Decision Tree scored 93.00% across metrics, demonstrating effectiveness when tuned. SVM and Logistic Regression both achieved 91.00% accuracy, with SVM excelling in precision at 93.75%. MLP performed the worst, with 89.00% accuracy and 87.00% recall. These results highlight ensemble methods, especially stacking, as effective in classification. A multi-class ROC curve in Figure 26 shows the Stacking Classifier's superior discriminative ability with perfect AUC per class. Random Forest also performed well with AUCs up to 1.00. Although Underweight had a slight AUC reduction, SVM and Logistic Regression had high AUCs of 0.97 and 1.00. The multilayer Perceptron showed high class separability with AUCs of 0.98-0.99, though overall precision was lower. Decision tree models also performed well, with minor weaknesses in the Underweight class (AUC 0.92), possibly indicating sensitivity issues.

Table 18: Hyper Parameter Tuning Table

Model	Hyperparameter
Logistic Regression	*C: 18.84106937218545, solver: saga*
Random Forest	*max_depth: 3, min_samples_leaf: 3, min_samples_split: 5, n_estimators: 50*
Decision Tree	*min_samples_split: 20, min_samples_leaf: 7, max_features: sqrt, max_depth: 10, criterion: entropy, ccp_alpha: 0.05*
SVM	*C: 10, gamma: scale, kernel: linear*
MLP (Neural Network)	*hidden_layer_sizes: (100, 50), activation: tanh, alpha: 0.028510645815734797, learning_rate: constant*
Stacking Classifier	*estimators=base_models, final_estimator=meta_model, n_jobs=-1*

Table 19: ML Models' Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
MLP	89.00	92.20	87.00	89.07
SVM (Pre-Optimization)	91.00	93.16	90.71	91.62
Decision Tree	93.00	93.00	93.00	93.00
Random Forest	98.00	97.00	97.87	97.32
Logistic Regression	91.00	93.75	88.51	90.58
Stacking Classifier	**99.00**	**99.20**	**96.67**	**97.77**

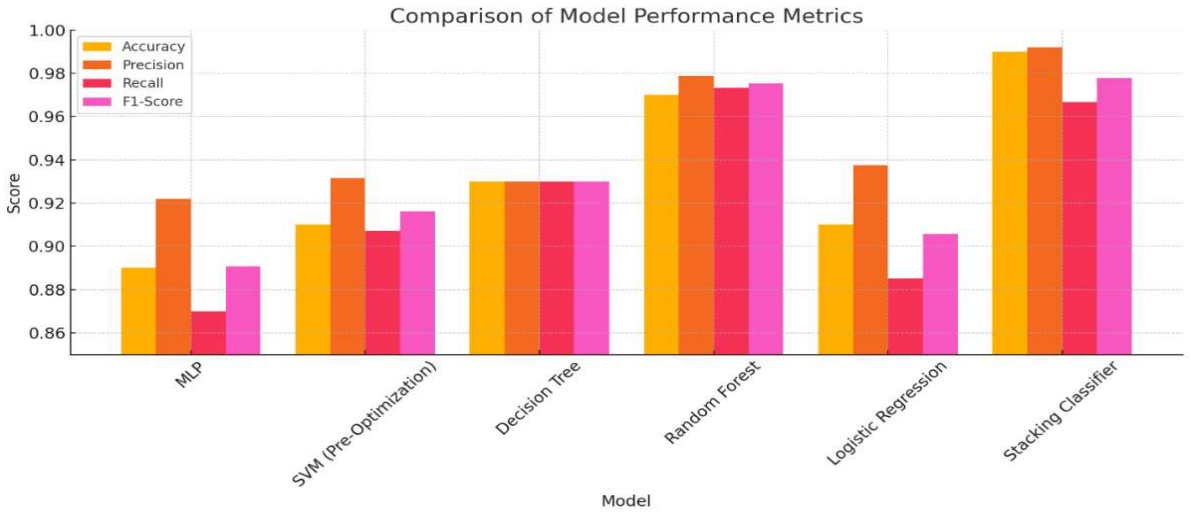


Figure 25. Comparison Chart of ML Models' Performance Matrices

5. Proposed Classifier

The Stacking Classifier was chosen for its ensemble strength and classification ability, combining Logistic Regression, Decision Tree, and Multilayer Perceptron with a Logistic Regression meta-classifier. It achieved accuracy, macro precision, recall, and F1-score of 99.00%, 99.20%, 96.67%, and 97.77%, outperforming other methods. ROC analysis showed strong class separability across nutritional statuses, with AUCs from 0.98 to 1.00, indicating reliable classification stability. While Random Forest performed similarly, the Stacking

Classifier had a higher recall (96.67% vs. 95.79%)- crucial in health tasks to reduce false negatives. Five-fold cross-validation and resampling addressed class imbalance, confirming the model's robustness and suitability for classifying nutritional status.

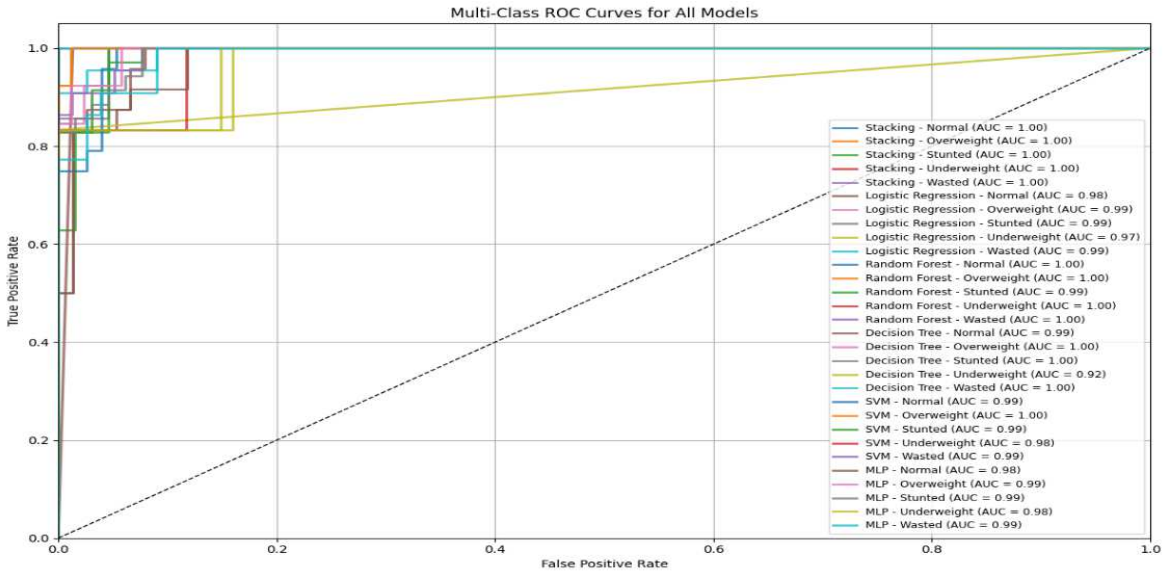


Figure 26. Comparison of ROC curves of ML Models

5.1 Explainability Analysis

Explainable AI (XAI) has two major categories, namely Global Explainability and Local Explainability, which are both specific to complex machine-learning models. Together, they provide additional insights into the decision-making process of such models. Using a systematic combination of global and local explanations, researchers and practitioners can attain predictive performance characterized by both accuracy and interpretability.

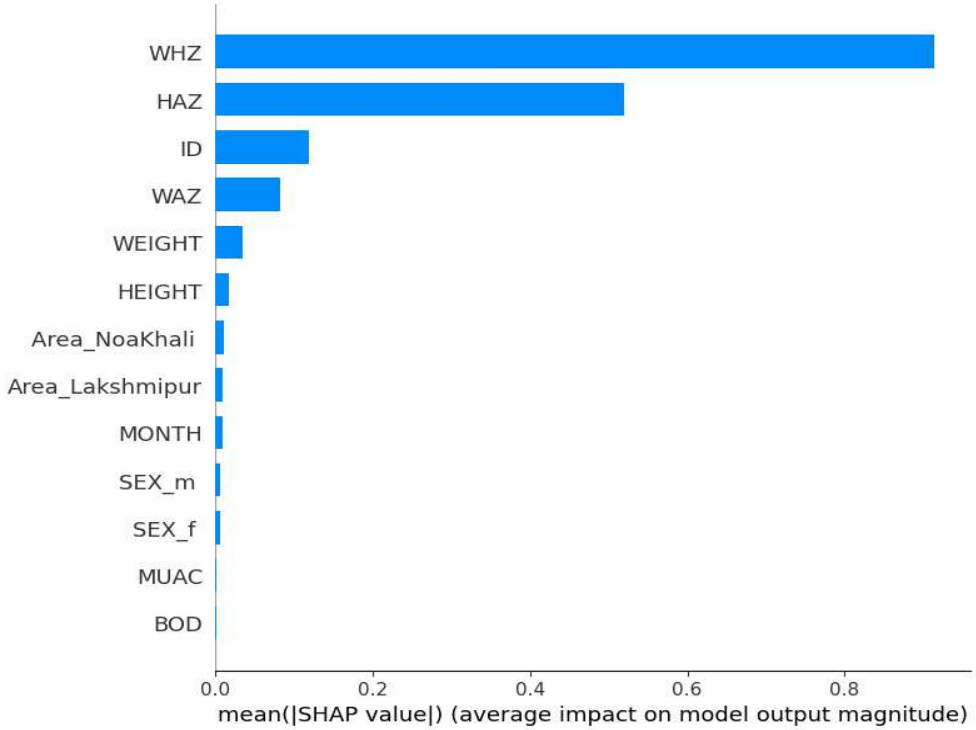


Figure 27. SHAP Feature Importance Plot Showing Average Impact on Model Output

5.1.1 Global Explainability

Figure 27 shows a SHAP summary plot (global explanations), which shows the mean value of how each feature has contributed to the model predictions. The two most dominant attributes, such as WHZ (Weight-for-Height Z-score) and HAZ (Height-for-Age Z-score), have a significant impact on the output of the model. Other variables like MUAC, SEX, MONTH, and geographical area (Noakhali, Lakshmipur) comparatively only have a slight impact. Attributes such as ID, WAZ, and weight have a medium effect. All of this taken together suggests that the ability of our model depends strongly on the presence of anthropometric indicators, in particular on WHZ and HAZ.

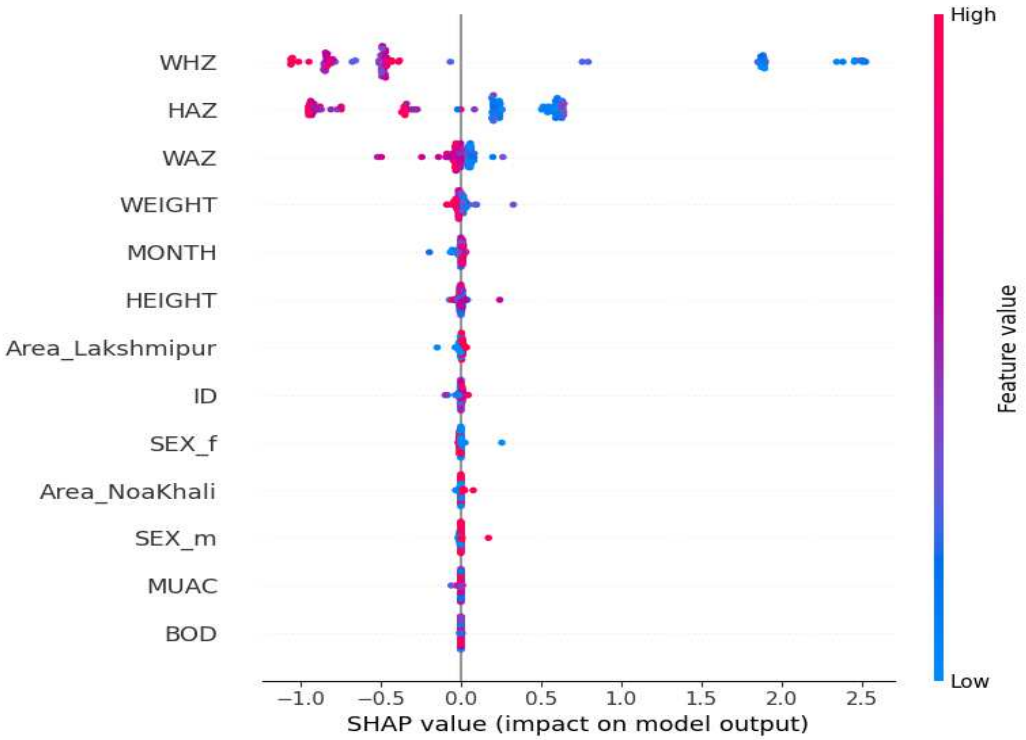


Figure 28. Impact on Model Output of Each Feature

Figure 28 shows the SHAP summary plot illustrating each component's impact on the model's predictions. WAZ has intermediate influence, while WHZ and HAZ are most significant with the highest average SHAP values. Features like Sex, location, BOD, and MUAC have minimal impact, as their values are near zero. The figure confirms the model primarily relies on major anthropometric indicators rather than demographic or regional factors, supporting its biological basis. Figure 29 presents the SHAP stacked force plot, demonstrating how individual features influence predictions across instances. Blue sections push the prediction towards malnourished groups, red sections towards healthier categories. The strongest features are WHZ and HAZ; high values indicate better nutritional status; low values suggest poorer status. Segment height and width show each feature's contribution strength and influence of growth indicators in the model.

5.1.2 Local Explainability

Figure 30 shows a SHAP force plot for a single instance, depicting feature SHAP values when a Stacking Classifier predicts 1.94 before contribution. Positive WAZ and HAZ increase the nutritional category, while negative WHZ decreases it. The final forecast is 2,00, indicating

improved accuracy. These results highlight the importance of anthropometric features in individual classification. Figure 31 displays a SHAP force plot explaining how feature contributions led to the prediction. Starting at a baseline of 1.84, WHZ significantly boosts the prediction (red bar), while HAZ's influence is minor and slightly negative (blue bar). Together, these produce a total prediction of 4.00, supporting confident classification into a better nutritional group, with WHZ being a key influential factor.

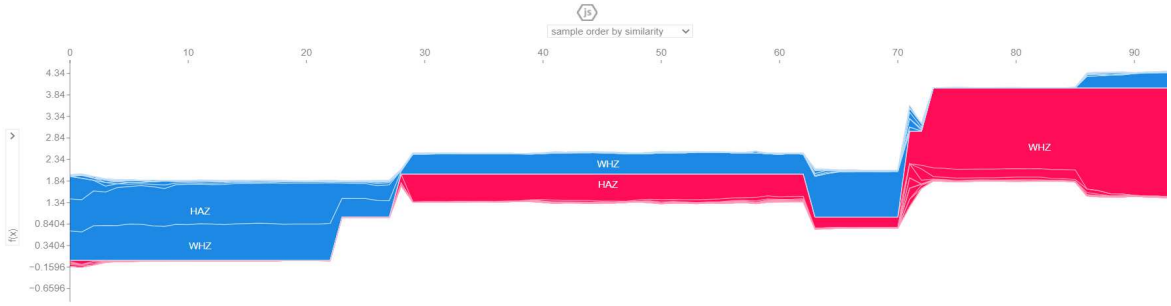


Figure 29. SHAP Force Plot

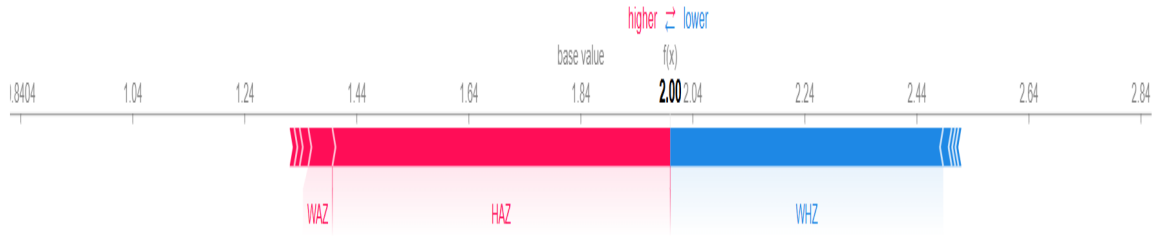


Figure 30. SHAP Force Plot of Stacking Classifier



Figure 31. SHAP Force Plot of Stacking Classifier

Figure 32 LIME shows one prediction of the stacking classifier with a 0.99 probability, classifying the instance as class 2. Key features include WHZ (> -0.86), ID (≤ 64.00), MUAC (≤ 13.50), and WAZ (> -1.89). Negative contributors were low height, sex (male), and specific locations. Overall, WHZ, ID, and MUAC were crucial, confirming the model's local reliability and alignment with global trends. Figure 33 indicates high confidence (0.99) in class 2, with WHZ > 0.86 and WAZ > 0.11 being strong positive factors. Notably, Area_Lakshmipur > 1.00 and ID ≤ 64.00 contributed positively. Minor negative effects came from month, weight, and HAZ, but didn't affect the outcome. Important nutritional indicators include WHZ (0.56), HAZ (0.69), and MUAC (1.22). The plot in Figure 34 shows 0.99 confidence that the instance falls in class 4, influenced mainly by negative contributions from WHZ (0.86) and Area_Lakshmipur. WAZ, HAZ, MUAC, and BOD also contributed negatively. Despite positive scores for HEIGHTS, WEIGHT, and HAZ, there weren't enough to offset the negative scores. Overall, the plot accurately distinguishes severe nutritional deficiency based on key growth indicators.

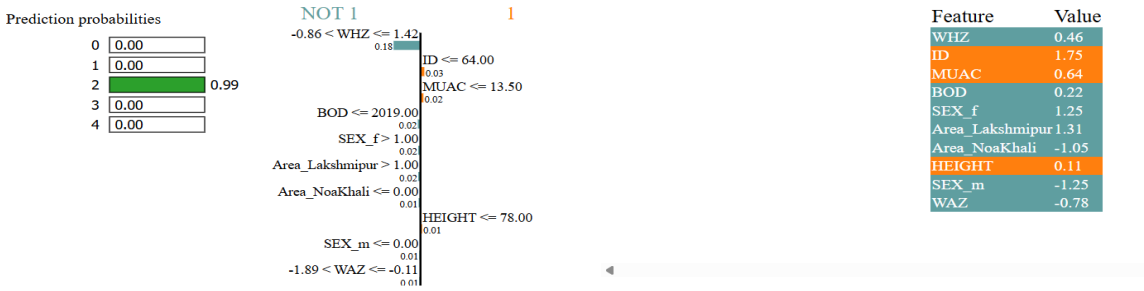


Figure 32. LIME Explanation for Class 2 Prediction – Influence of ID and MUAC

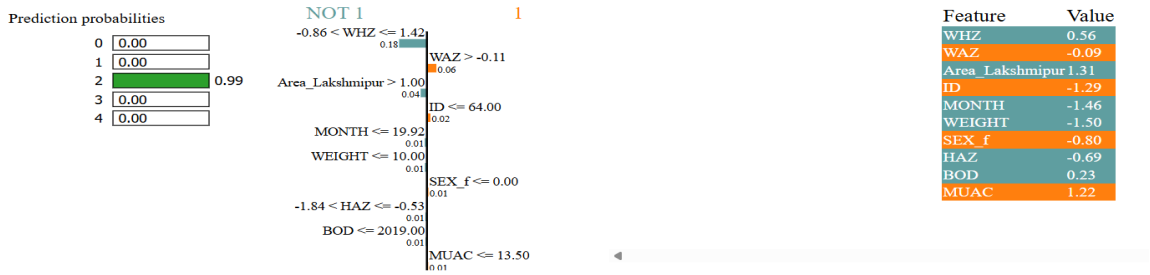


Figure 33. LIME Explanation for Class 2 Prediction – Emphasis on Age and Nutritional Metrics

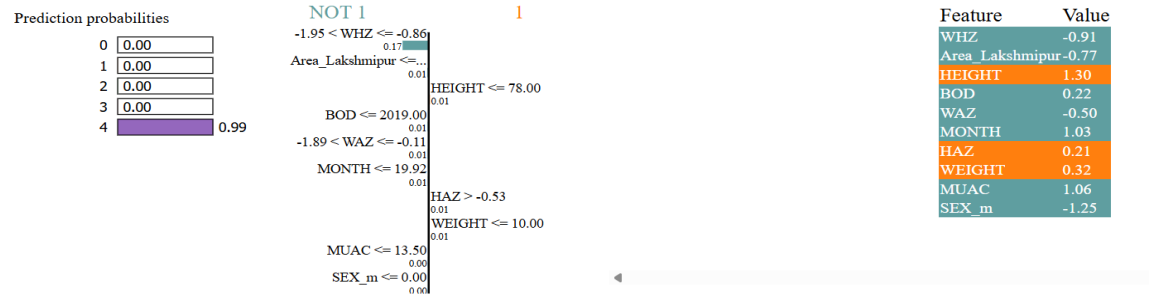


Figure 34. LIME for Local Explainability Stacking Ensemble Model (class 4)

5.2 Discussion

Malnutrition is one of the most significant public health issues in Bangladesh, especially among children between the ages of 1 and 5 years. Traditional assessment methods are lengthy, resource-intensive, and time-consuming; hence, the large-scale screening is challenging in under-resourced settings. In recent years, machine learning enabled methods have been developed that provide faster, scalable, and more accurate assessments of nutritional status.

This study aims to identify the presence of malnutrition using a machine learning-based method that can produce a faster, scalable, and prospectively more accurate evaluation of nutrition status. The individual models had different accuracies in our experiments, such as MLP (89%), SVM before optimization (91%), Decision Tree (93%), random forest (98%), and Logistic Regression (91%). In comparison, the proposed stacking classifier was 99% accurate relative to every individual model, proving that an aggregate of different learners is worthwhile. Furthermore, the model demonstrated an accuracy of 99.20%, a recall of 96.67%, and an F1-score of 97.77%, proving once again the effectiveness of combining different learners into the same framework and outperforming individual models.

Table 20: Comparative Analysis with Existing Works

Authors	Methods	Dataset Used	Acc. (%)	Prec. (%)	Recall. (%)	F-1 score (%)	ROC-AUC (%)
Our study	***Stacking Classifier***	***Collected***	***99.00***	***99.20***	***96.67***	***97.77***	***99.00***
Liangyu Yin et al. [26]	Multinomial Logistic Regression (MLR)	INSCOC study (2011–2020), 14,134 cancer patients, China	99.90	95.00	96.90	98.81	99.00
Mukesh Vishwakarma et al. [17]	Gradient Boosting Classifier 5-fold CV	NFHS-5 (2019–2021), 232,920 children, India	65.00	40.00	59.00	49.00	70.00
Sabbir Ahmed Hemo et al. [11]	Decision Tree & Random Forest	BDHS 2014 (Bangladesh)	70.10	45.04	59.10	72.80	69.80
Rendra Gustriansyah et al. [13]	Random Forest (RF)	Kaggle toddlers' dataset, 200 samples	97.37	95.00	98.81	99.00	99.00
Eric Komla Anku et al. [2].	XGBoost	MICS Ghana dataset	98.00	90.00	99.00	98.00	98.00
Md. Merajul Islam et al. [14]	MLR + Random Forest (RF)	BDHS 2014 (Bangladesh), 15,464 women aged 15–49	81.40	88.10	89.80	91.50	83.70

Compared to earlier studies in Table 20, the more obvious results are easy to understand. The accuracy reported by Mukesh Vishwakarma et al. was 65%, using a Gradient Boosting Classifier, likely due to data complexity and feature variability [17]. In contrast, Sabbir Ahmed Hemo et al. achieved 70.10% with Decision Tree and Random Forest, although limited preprocessing and class imbalance could restrict these results [11]. Rendra Gustriansyah et al. reached 97.37% with Random Forest on a smaller dataset that made pattern recognition simpler [13]. Conversely, Eric Komla Anku et al., using the boosting algorithm, reported a 98. 00% accuracy score with XGBoost, demonstrating the model's ability to handle complex interactions, although in a different demographic group [2]. Similarly, Md. Merajul Islam et al. attained 81.40% accuracy with a hybrid MLR- Random Forest approach, where suboptimal feature selection and class imbalance are likely to limit performance [14]. Another study achieved 99.95% accuracy with Random Forest after specific dataset preparation and result

formulation [32]. The prediction of stunting, wasting, and underweight in Rahman et al. showed an accuracy of 88.3%, 87.7%, and 85.7%, respectively, with better results for stunting [39]. Fikrewold et al. reported 69.8% for stunting (using xgbTree), 90.2% for wasting (using GLM), and 76.7% for underweight (using NNet), indicating variable results across measures—similarly, Md. Mehrab Shahriar et al. found wasting to be most predictable at 86%, with underweight at 70% and stunting at 67.3% [34,8]. Several other studies reported moderate accuracy ranging from 70.1% to 98%, influenced by dataset characteristics, feature specifications, and malnutrition indicators [30, 41, 35, 46]. Overall, the stacking classifier in our study outperforms previous models by combining multiple base learners, effective preprocessing, and handling class imbalance, achieving superior predictive performance in the Bangladeshi context. This ensemble uses logistic regression, decision trees, and multilayer Perceptrons (MLP) as base learners, and logistic regression as the meta-learner. The main advantage of this approach lies in the diversity of learning strategies: tree-based methods, neural network control, and linear separation- improving overall prediction accuracy and reducing individual component limitations. The results show that ensemble machine learning methods are crucial in identifying malnutrition and provide precise, scalable, and practical solutions for addressing malnutrition at the population level.

Additionally, our model employs explainability tools like SHAP and LIME, highlighting that WHZ is the most essential feature. The WHZ value plays a key role in identifying nutritional status in this study. Also, a web-based framework has been developed based on the proposed model for enabling faster prediction of nutritional status. This setup allows healthcare providers to quickly predict children's nutritional status and assist in timely interventions. It is also suitable for use where the proper resources are not available.

Overall, the proposed stacking ensemble model is effective in prediction, generalization, and explainability, making it a promising tool for detecting malnutrition in children in Bangladesh. Its transparency through SHAP and LIME, along with its ability to be quickly implemented with scalability via a web-based framework, emphasizes its importance for timely interventions to research malnutrition and shape public policies.

6. API Deployment

The Malnutrition Assessment System employs a robust two-tier architecture with a Go-based frontend and a Python-based backend. It provides comprehensive nutritional analysis for children by combining traditional anthropometric Z-score assessments with machine learning predictions to deliver actionable insights. The system integrates a FastAPI-based Python backend and a Go frontend to offer AI-driven and traditional dietary evaluations. The API workflow is illustrated in Figure 35 of the original paper, adapted accordingly.

The backend is implemented in Python and is built on the FastAPI framework to deliver a trained machine learning model (ensemble_model.pkl). It gets input through the/predict endpoint, which has the age, weight, height, MUAC, gender, location, and Z-scores (WAZ, HAZ, WHZ). The model generated a prediction of whether an individual is malnourished or not after processing the input data using NumPy and validating that data using Pydantic.

FastAPI, Pydantic, Joblib, and NumPy are key tools. The GitHub address is "https://github.com/Sanjida1-cell/Malnutrition-Prediction-python-service".

A Go frontend utilises a web-based form to enter user data and initially carries out a conventional nutritional evaluation against WHO standards of growth stored in Excel documents. It computes Z-scores and estimates an initial state (e.g., Normal, Stunted, Wasted). Such information is then transmitted to the Python backend. The GitHub address is "https://github.com/Sanjida1-cell/Predicting_malnutrition".

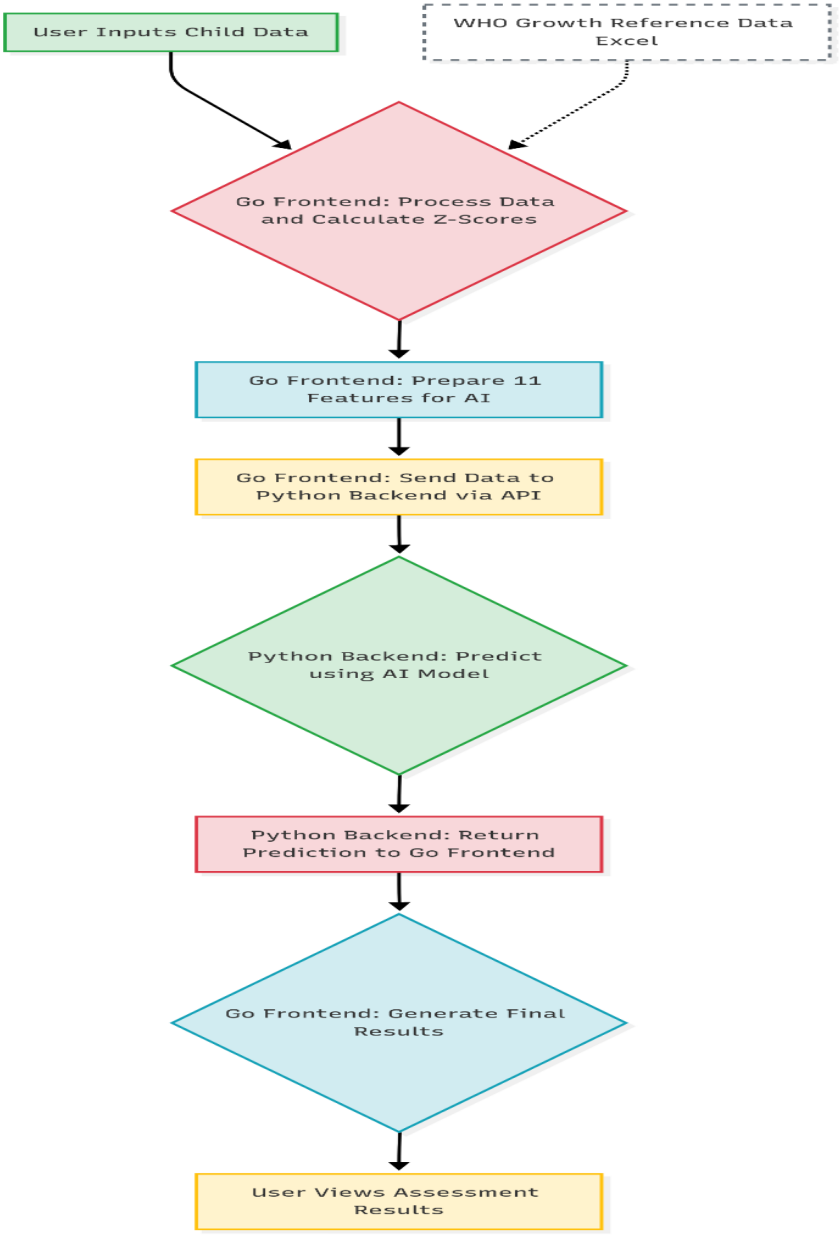


Figure 35. Workflow diagram of Malnutrition Detection System

Project Showcase

Figures 36 and 37 show the input form interface and the output result of the Go frontend application. Users can enter their age, weight, height, MUAC, gender, and location information. After uploading, the data is sent through the API connection to the FastAPI backend, where a pre-built machine learning model reads it. The model is saved as a .pkl file

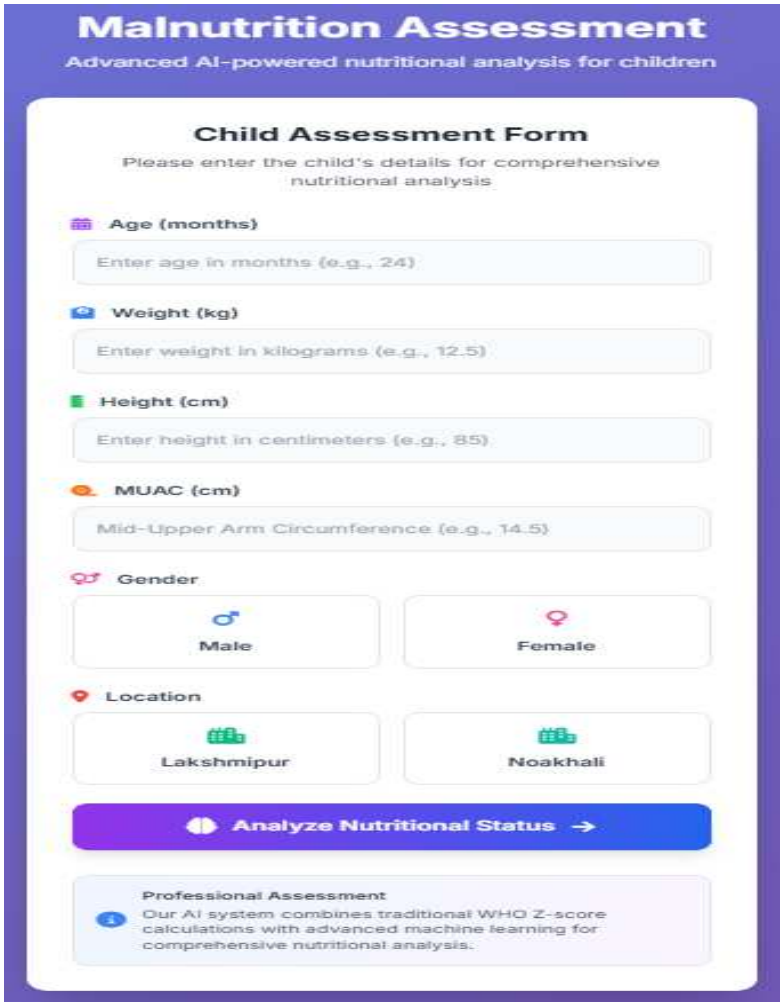


Figure 36. Children's Data Input Form

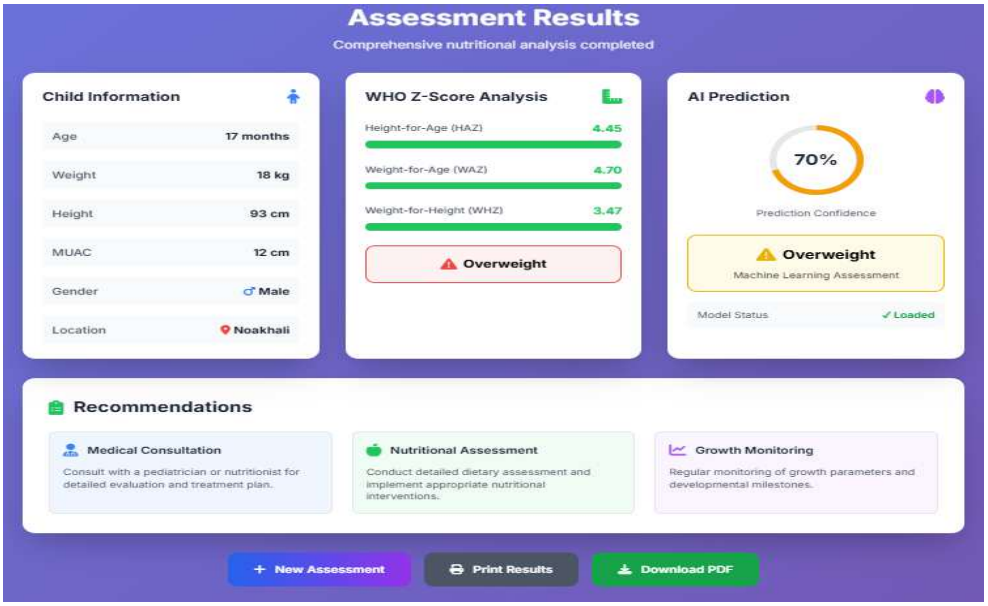


Figure 37. Child's Malnutrition Assessment (Output)

and generates real-time predictions. This result is passed back to the front end, where users can see their nutritional status in real-time. The output displays two results: a calculated prediction

using the WHO standard range and a model-predicted result with confidence. It also provides recommendations based on nutritional status. This architecture ensures a smooth data flow between the frontend and backend models, creating a user-friendly platform that's web-compatible with mobile environments.

Strengths

The greatest strength of this research paper is the development of a stacking ensemble model that combines Decision Tree, Multilayer Perceptron (MLP), and Logistic Regression models as base learners, with Logistic Regression serving as the meta learner. Additionally, SHAP and LIME are used to interpret the model, and a conceptual web-based framework has been designed to ensure rapid and scalable prediction of malnutrition.

Limitations

This study has limitations despite obtaining favorable results. The data were region-specific (Noakhali and Lakshmipur), and the dataset is medium-sized, which could restrict the model's generalizability to other regions or socio-economic contexts within Bangladesh. The dataset mainly focused on anthropometric parameters and did not include other factors that could improve prediction accuracy, such as diet intake, maternal health, or socio-economic conditions. Although the stacking ensemble showed good performance, exploring more advanced algorithms or incorporating temporal and longitudinal data was beyond the scope of this work. Additionally, the conceptual web-based framework could be enhanced to offer stage-specific recommendations, like medical consultations only when needed, based on nutritional assessment and growth monitoring. It has not yet been developed into a mobile application, which limits accessibility.

Advantages

The research study provides vital recommendations to policymakers for developing interventions to combat child malnutrition in Bangladesh. The stacking ensemble model enables the prediction of the nutritional status of a child, and the framework helps healthcare experts to offer early and stage-specific advice, and it facilitates quick and scalable assessment. It will be upgraded into a mobile app, which, once deployed, will improve accessibility across the nation. Additionally, the government can use the key features identified, such as WHZ, HAZ, and WAZ, to guide targeted policies and resource distribution.

7. Conclusion

Bangladesh goes through a severe problem of malnutrition, especially amongst children below the age of five years, which raises issues of the future of the overall health of a nation, besides the economic growth of the country. To address this problem, the current research endeavored to create an efficient stacking ensemble model that could be used to anticipate the nutritional status of young children based on some of the essential anthropometric measures, such as weight-for-age Z-score (WAZ), height-for-age Z-score (HAZ), weight-for-height Z-score (WHZ), and mid-upper arm circumference (MUAC).

The stacking model combined the powers of three classifiers, including Logistic Regression, Decision Tree, and Multilayer Perceptron (MLP). This mixture resulted in very accurate and consistent predictions, and its accuracy level was as high as 99%, indicating its potential as a trustworthy diagnostic tool. Also, a layer of interpretability was provided by the implementation of explainable AI methods, including SHAP and LIME, which allowed distinguishing which features had the most significant impact on each prediction. These interpretations indicated that anthropometric measures connected with growth were found to affect the prediction results with significantly more influence than the demographic variables or geographic variables. Overall, the present piece highlights possibilities of ensemble machine learning methods not only to enhance early malnutrition detection but also to inform decision-making in low-resource environments. The composite of predictive accuracy and interpretability makes the model practical and implementable in addressing malnutrition in children in Bangladesh and other places with similar issues.

Future Scope

- Use larger and more diverse datasets from across Bangladesh.
- Include additional variables (diet, maternal health, environment, socio-economic status).
- Utilize longitudinal or time-series data for trend monitoring.
- Explore advanced ensemble methods (Gradient Boosting, XGBoost).
- Apply neural network architectures for complex patterns.
- Support early detection and timely intervention of malnutrition cases.

Acknowledgements
We sincerely thank all the children and their legal guardian(s) who willingly provided information for our study.

Availability of data and materials
Data is provided within the supplementary information files.

Declarations

Funding
There was no funding to complete this research work.

Clinical Trial
Clinical trial number: not applicable.

Ethics Approval
This study did not include any experiments involving humans or animals. Ethical clearance was granted by the Ethics Committee of Noakhali Science and Technology University (reference no. NSTU/ET/EC/2024/98).

Consent to Participate

Informed consent was gathered from all participating children and their legal guardians prior to data collection.

Consent to Publish

The legal guardian(s) of participating children verbally consented to the use of survey data for research purposes, with no identifiable information disclosed in the published results. Consent was obtained during the survey through questions asked by the enumerator, without requiring signed or written documentation. The analysis ensured that no personal or sensitive information about the children was reported.

Competing interests

The authors declare no competing interests.

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