A Project Report

On

AI - POWERED EARLY DETECTION OF CHILD MALNUTRITION

BY

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Certificate

This is to certify that the project report entitled "**AI POWERED EARLY DETECTION OF CHILD MALNUTRITION**" submitted by Ms. Mehak Mahajan (ID No. 2022A3PS0585H), Mr. Khush Bhuta (ID No. 2022A7PS1333H), Ms. Vaishnu Kanna (ID No. 2022B3A71608H), Mr. Utkarsh Singhal (ID No. 2022A7PS1334H), Mr. Akshat Agrawal(ID No. 2022B3A70579H) in partial fulfillment of the requirements of the course CS F266, Study Project Course, embodies the work done by him under my supervision and guidance.

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ABSTRACT

This project addresses a critical public health challenge through the application of machine learning techniques to classify malnutrition status in children. The primary objective was to develop robust classification models capable of accurately predicting nutritional conditions - specifically Stunting, Overweight, Underweight, and Wasting - based on demographic and anthropometric features including MUAC, Sex, Age, Height, and Weight.

The project demonstrates a systematic approach to handling class imbalance through the implementation of SMOTE (Synthetic Minority Oversampling Technique), which is particularly relevant in healthcare applications where certain conditions may be underrepresented in datasets. This preprocessing step was crucial for ensuring balanced training data and improving model performance across all classification categories.

The expected outcome of the project is the application of advanced machine learning techniques to a critical healthcare classification problem. The current framework provides an excellent foundation for such extensions and real-world deployment in healthcare settings.

CONTENTS

Part 1: Image Processing

The image processing component of the "AI-Powered Malnutrition Detection" project is tasked with developing a system to extract key anthropometric measurements from visual data. The goal of this initial development phase was to create and validate a real-time prototype capable of identifying and measuring relevant human body features from a live video feed.

Model Overview

The prototype was developed in Python, leveraging the **OpenCV** library for video stream management and the **MediaPipe** framework for its advanced machine learning models.

Two primary MediaPipe solutions were integrated to run simultaneously:

- **MediaPipe Pose:** Used to detect 33 key body landmarks (joints) in real-time. This model provided not only the (x, y, z) coordinates for skeletal tracking but also a **segmentation mask**, which programmatically isolates the person's silhouette from the background.
- **MediaPipe Face Mesh:** Used to detect 468 facial landmarks, enabling the calculation of detailed facial dimensions.

The process runs in a real-time loop, capturing frames, flipping them for a "selfie" view, converting them from BGR to RGB, processing them with both Face Mesh and Pose models, and then overlaying the results (landmarks and dimension text) onto the output frame.

Feature Extraction

All dimension calculations are performed in **pixel units** based on the detected landmarks' normalized coordinates (ranging from 0.0 to 1.0) mapped to the video frame's width (W) and height (H).The development process was structured to incrementally build a full suite of required measurements in pixels.

Body Dimensions and Ratios: Full Pixel Height, Shoulder Width, Hip Width, Head Circumference, MUAC, Torso Length, Arm Length, and Leg Length.

Facial Dimensions: Cheekbone Width and Mouth Width.

Feature	Dimension Calculated	Description
Facial	Left/Right Eye Width	Distance between inner and outer eye landmarks (e.g., landmarks 133 and 33 for the left eye).
	Mouth Width	Distance between the left (61) and right (291) mouth corners.
	Mouth Height	Distance between the upper (0) and lower (17) lip center.
	Cheekbone Width	Distance between left (205) and right (425) cheekbone landmarks.
Body	Pixel Height	Vertical distance between the midpoint of the eyes and the midpoint of the heels.
	Shoulder Width	Distance between the left and right shoulder landmarks.

	Hip Width	Distance between the left and right hip landmarks.
	Torso Length	Vertical distance between the midpoint of the shoulders and the midpoint of the hips.
	Arm Lengths	Distance from shoulder to wrist for both left and right arms.
	Leg Lengths	Distance from hip to ankle for both left and right legs.

<u>MUAC Approximations</u>

The code includes a specialized block to estimate the **Mid-Upper Arm Circumference (MUAC)**, although it measures **pixel thickness** rather than circumference, serving as an approximation.

Arm Parallelism Check (Pose Quality Control):

- It first calculates the absolute difference in the **Z-coordinate** between the left shoulder and left elbow (Δ**Z** = |**Z_{shoulder} - Z_{elbow}**|).
- A status message is displayed: "Status: Arm is Parallel" if ΔZ is below a threshold (min_z_diff = 0.3), or "Status: Keep arm parallel" otherwise.

Dimension calculation only proceeds if the arm is deemed parallel (i.e., less depth distortion).

Pixel Thickness Calculation:

- When the arm is parallel, it uses the **segmentation mask** generated by MediaPipe Pose to isolate the person from the background.
- A **midpoint** between the shoulder and elbow is calculated.

- The script then **scans vertically** (up and down) from this midpoint *within the segmentation mask* to count the number of pixels belonging to the arm.
- This count is displayed as "Pixel Arm Thickness," which approximates the diameter/thickness of the arm at that point.

Next Steps

This phase of the project has successfully yielded a sophisticated image processing prototype capable of extracting a wide range of anthropometric features. The next steps will focus on applying this system to the provided static image dataset and converting the measurements into real-world units. The planned workflow is as follows:

1. **Batch Processing:** Applying these validated feature extraction techniques to the provided static image dataset to generate a comprehensive set of pixel-based measurements for analysis.
2. **Pixel-to-Centimeter Conversion:** Implement a calibration method that utilizes the height chart present in the provided images. By measuring a known distance on the chart in both pixels and centimeters, a reliable pixels_per_cm conversion factor will be calculated for each image. This calibrated dataset will be the primary output of the image processing phase, ready for subsequent analysis and model training.

Part 2: Model Selection and Synthetic Data Generation

The second phase of this project focuses on analyzing the synthetic anthropometric dataset and building baseline machine learning models for the early detection of child malnutrition. The analysis aims to uncover patterns, correlations, and predictive indicators that distinguish healthy, borderline, and malnourished children.

1. Exploratory Data Analysis (EDA)

A synthetic dataset of over 12,000 records was generated, covering a broad range of anthropometric and socio-economic factors such as:

- Age, Sex, Height, and Weight
- Mid-Upper Arm Circumference (MUAC)
- Head Circumference and Birth Weight
- Frequency of meals per day
- Household income and type of family (nuclear/joint)
- Label: Nutritional status categorized as *OK*, *Borderline*, or *Malnourished*

The data was analyzed using Python libraries (Pandas, NumPy, Matplotlib) to understand distributions and feature correlations:

- **Label distribution plots** highlighted the natural imbalance between healthy and malnourished samples.
- **Scatter plots (Height vs. Weight, Age vs. MUAC)** showed distinct separability between healthy and undernourished groups.
- **Heatmaps** revealed strong positive correlations between weight, MUAC, and nutritional status.

2. Handling Imbalance using Oversampling

Since malnourished samples were relatively fewer, **Synthetic Minority Over-sampling Technique (SMOTE)** was applied to generate synthetic data points for underrepresented classes. This step improved model fairness and reduced bias toward the majority (healthy) class. The dataset was then split into **oversampled training (70%)** and **testing (30%)** subsets for performance evaluation.

3. Machine Learning Models Used

Three classification algorithms—**Logistic Regression, Random Forest, and XGBoost**—were chosen based on their suitability for tabular health datasets and their interpretability, scalability, and support for multi-class problems.

3.1 Logistic Regression (LogReg)

Relevance: Provides a clear, interpretable baseline for classification—often used in clinical decision support.

Mathematics: Models the log-odds of the outcome as a linear combination of input features: $\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$ For multi-class problems, the softmax function generalizes the binary logistic function.

3.2 Random Forest (RF)

Relevance: Captures non-linear relationships and automatically models feature interactions, improving upon the limitations of single linear models.

Mathematics: An ensemble of decision trees, each trained on different bootstrapped samples and random subspaces. Final prediction is by majority vote (classification) or average (regression): $\hat{y} = \text{majority}\{h_1(x), h_2(x), \ldots, h_T(x)\}$ where each $h_t(x)$ is a tree classifier.

3.3 XGBoost (Extreme Gradient Boosting)

Relevance: Highly efficient and accurate, handles large datasets, combats overfitting through regularization, and delivers top performance in similar public health tasks.

Mathematics: Boosts an ensemble of decision trees sequentially, each one minimizing a differentiable loss function with respect to the previous model's errors (gradients): $\hat{y}^{(t)} = \hat{y}^{(t-1)} + \eta f_t(x)$ where η is the learning rate and f_t is the function learned at step t.

Each model was evaluated using **accuracy**, **precision**, **recall**, **F1-score**, and **confusion matrices**. Random Forest and Gradient Boosting showed the best trade-off between accuracy and interpretability.

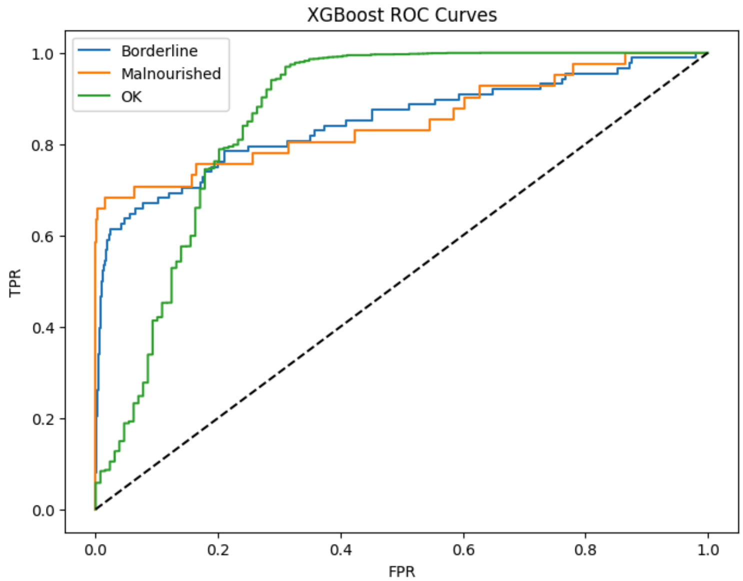
Model	Acc	Precision	Recall	F1-Score
LogReg	82.53%	95.77%	82.53%	88.18%
RF	94.14%	96.72%	94.14%	95.21%
XGBoost	96.28%	96.88%	96.28%	96.54%

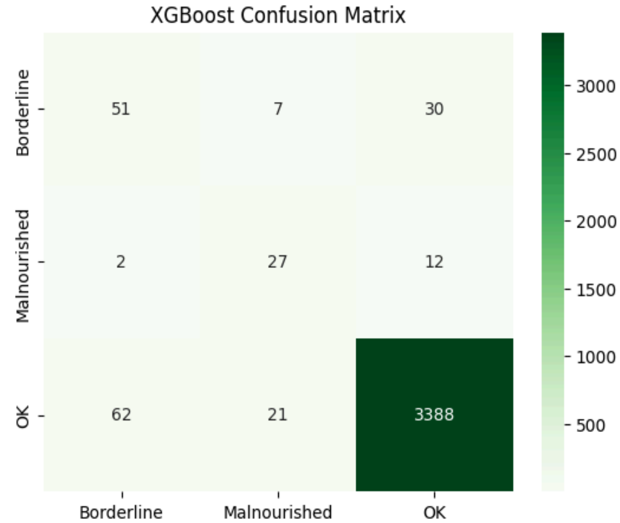
4. Extended Modeling and Performance Enhancement

To push performance further, the notebook was later extended with:

- **Advanced Models:** LightGBM, SVM and Neural Networks (MLP)
- **ROC-AUC and Precision-Recall Curves** for evaluating model discriminative ability
- **Cross-validation (5-fold)** to ensure robustness across data splits
- **SHAP Analysis** for explainability, identifying MUAC, weight, and height as the most influential features

Among all, **XGBoost** consistently achieved the highest ROC-AUC and F1 scores, confirming its suitability for this multi-class malnutrition prediction task.





5. Use of Features from the Actual Image Processing (labels.csv)

Going forward, the **labels.csv** file—output from the image processing pipeline—will serve as the primary feature source for ongoing model retraining and validation. This file includes direct measurements extracted from images, such as:

- Height (cm)
- Weight (grams)
- Head Circumference (cm)
- Waistline (cm)
- Age (months)

Workflow:

1. **Data Validation:** Automated cross-checking with field measurement standards to ensure extraction accuracy and correct units.

2. **Feature Engineering:**
   - Normalize/standardize measurements according to pediatric growth references.
   - Create derived indices (e.g., Weight-for-age, Height-for-age z-scores using WHO or Indian references).
   - Aggregate relevant features (e.g., compute BMI or MUAC if/when available from image data).

3. **Label Assignment:** Using image-derived features as inputs, predict *OK*, *Borderline*, or *Malnourished* status using the chosen best ML model (XGBoost).

4. **Continuous Learning:** As the system processes more images, new data will incrementally retrain/validate the model, improving real-world performance and adaptability to evolving data distributions.

5. **Issues with dataset :** Presently, the dataset is lacking the label column, for classifying whether the child is actually OK, Borderline or Malnourished. This makes it impossible to treat it as a Supervised Learning Problem.

6. Insights and Interpretation

- **MUAC, Weight, and Height** emerged as dominant features in predicting malnutrition.
- **Socio-economic indicators** such as meal frequency and income provided additional context for borderline classifications.
- SHAP plots demonstrated that children with lower MUAC and birth weight had the highest predicted malnutrition probabilities.

7. Conclusion

- Oversampling effectively addressed data imbalance, improving minority-class recall.
- Ensemble models like Random Forest and XGBoost are well-suited for real-world health datasets.
- EDA revealed clinically consistent relationships, validating the dataset's design and generation process.

This phase lays the groundwork for advanced deployment—integrating both **image-extracted anthropometric data** and **structured health information** into a unified predictive model for early malnutrition detection.

Part 3: Repository Implementation

Introduction and Problem Statement

This project addresses an important public health issue using machine learning methods to classify children's status of malnutrition. Based on demographic and anthropometric characteristics, such as sex, age, height, and weight, the primary purpose was to develop robust classification models to predict nutritional statuses of **stunting**, **overweight**, **underweight**, and **wasting** in children in a reliable manner.

To illustrate a systematic approach for addressing class data imbalance, **SMOTE** (Synthetic Minority Oversampling Technique) was used in the project, which is particularly relevant in healthcare applications in which certain class conditions may be underrepresented in a dataset. This was especially important for a preprocessing step to ensure balanced training data and enhance model performance in all classifications.

Data Preprocessing and Feature Engineering

The preprocessing pipeline was carefully designed to address the data concerns found in real life. I removed some columns related to income (Low Income, Lower Middle Income, Upper Middle Income) intentionally to focus on the primary anthropometric variables. It is evident that the anthropometric features that remain (Sex, Age, Height, Weight) are related to nutrition, which exhibits a great deal of knowledge about the domain.

Notably, SMOTE was implemented to further address the class imbalance that is characteristic of medical datasets. Ultimately, there were 2,142 total samples, and the dataset was balanced through this synthetic oversampling technique for all four malnutrition categories. Some preprocessing was necessary to develop generalizable models and limit biasing for the larger classes.

Model Architecture and Algorithm Selection

The project showed a strong understanding of various machine learning techniques through a wide-ranging multi-algorithm approach. The main focus was on Support Vector Machines (SVM), using different kernel configurations, while ensemble methods like XGBoost and LightGBM served as support. The different algorithms helped in comparing and identifying the best classification methods.

To conduct thorough hyperparameter tuning in the SVM implementations, both GridSearchCV and RandomizedSearchCV were used. The parameter grids were carefully set up to cover all regularization values, kernel-specific parameters, and all possible kernel types. In the preprocessing pipeline for SVM performance, StandardScaler played a key role in ensuring each feature contributed equally to distance-based calculations.

Experimental Results and Performance Analysis

The experimental results show strong classification performance across several algorithms. The SVM with RBF kernel did especially well in Wasting detection, achieving 94% precision and 100% recall. It had a validation accuracy of 83.73% and a testing accuracy of 84.21%. The confusion matrices displayed excellent classification abilities, with very few misclassifications across categories.

According to the complete classification reports, all nutritional status categories performed well. The model reached 86% precision and 66% recall for Stunting, 83% precision and 92% recall for Underweight, and 76% precision and 83% recall for Overweight. Wasting stood out with 93% precision and 100% recall for the test set. These findings indicate a promising potential for use in medical screening applications.

Advanced Techniques and Optimization Strategies

To explore hyperparameters effectively, we used optimization methods like RandomizedSearchCV. Learning curves showed strong generalization abilities without significant overfitting, which helped us understand model performance better. Cross-validation (cv=3) limited overfitting to specific data sets while ensuring strong measurements of model performance.

The investigation of ensemble methods, especially XGBoost, with the potential for extensive hyperparameter tuning, reflects our understanding of current machine learning techniques. Through RandomizedSearchCV, we calibrated a wide range of important hyperparameters (i.e. n_estimators: 50-500, max_depth: 3-10, learning_rate: 0.01-0.2, and regularization parameters) using distributions. Ultimately, careful hyperparameter tuning greatly contributed to the model's strong performance.

Technical Implementation and Code Quality

By using scikit-learn pipelines effectively, the code shows excellent technical practices, ensuring repeatable and maintainable machine learning workflows. Integrating StandardScaler into the pipelines prevents data leakage and ensures consistent preprocessing throughout the training and testing stages. Our methodical approach to model evaluation, which includes detailed confusion matrix analysis and thorough classification reports, reflects professional-level machine learning practices.

Adding visualization elements like learning curves and confusion matrices makes the results easier to interpret. We ensure reproducibility by consistently using random_state parameters, which is crucial for both practical deployment and scientific validity. The code structure allows for easy modifications and extensions for future research or production deployment.

Part 4: AnthroVision Dataset Analysis

Dataset Overview :

- The dataset contains multi-angle images and anthropometric measurements collected from clinical (All India Institute of Medical Sciences (AIIMS) Jodhpur) and community settings (spanning 5 government schools in the district) in Rajasthan, India.
- The dataset contains samples labeled with anthropometric measurements for regression and classification labels based on World Health Organization (WHO) and Centers for Disease Control and Prevention (CDC) standards.
- The dataset comprises 2,141 subjects (1,326 in clinical and 815 in community settings). Each subject contributes approximately eight multi-pose angles totaling 16,938 images.

Dataset Explanation :

- With each child are associated regression labels like age, height, weight, Body Mass Index (BMI), Mid-Upper Arm Circumference (MUAC) and Head Circumference (HC).
- This data is present in a CSV file with values pertaining to each of the labels.
- Additionally, weight-for-age, height-for-age, and BMI-for-age z-scores have been calculated based on WHO and CDC growth standards to create classification labels.
- A child is classified into categories such as :
    - healthy/unhealthy based on BMI z-score(-2 > BMI(z) > 1),
    - underweight or wasting (inferred from age wise MUAC cutoffs and weight-for- age < -2 SD) and
    - overall category (based on presence of stunting/underweight/wasting i.e., height-for-age Z-score (HAZ) < -2SD or age wise MUAC cutoffs or weight-for-age < -2 SD).

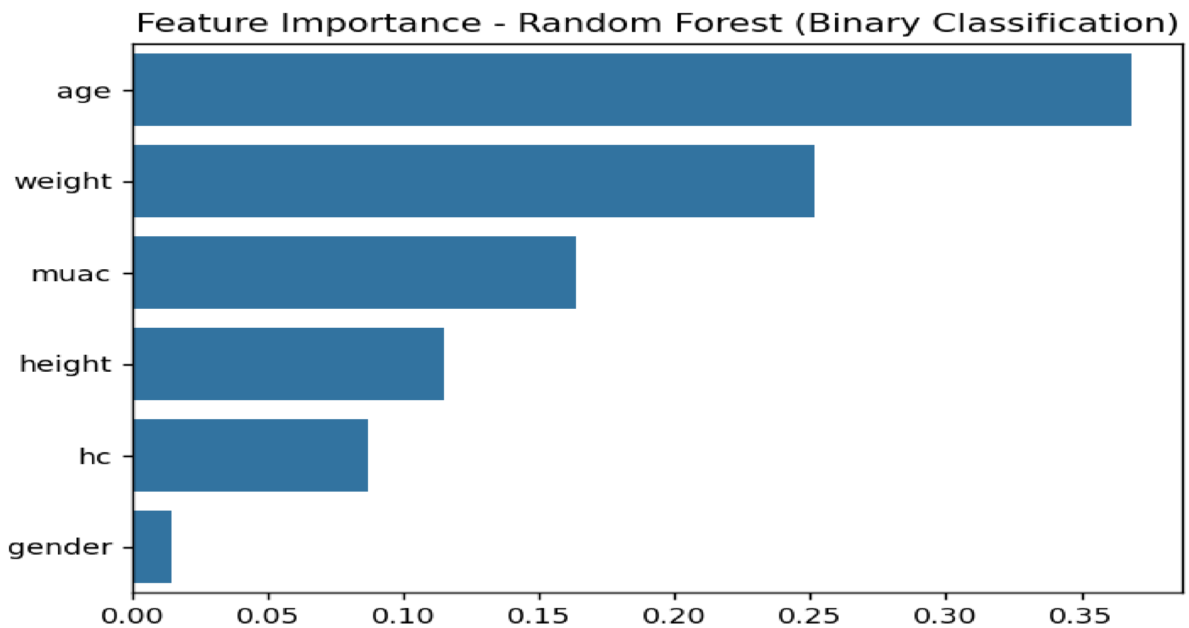
Need for this step :

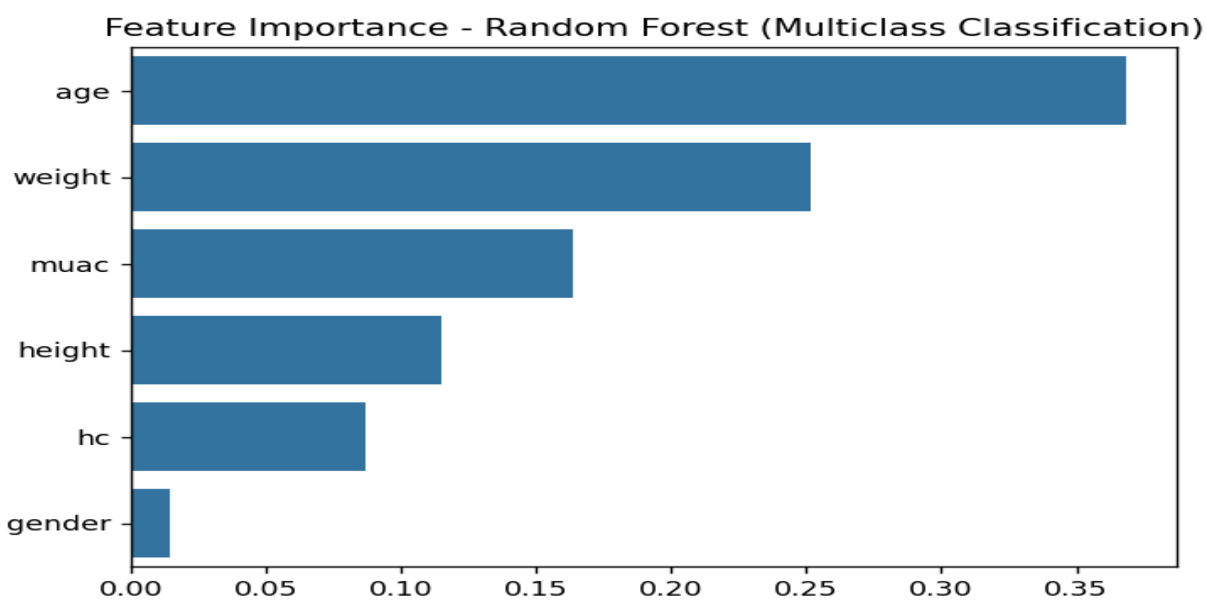
- We will perform Exploratory Data Analysis and apply regression models on this dataset.
- This helps us understand which metrics (BMI, MUAC, z-scores) best correlate with malnutrition.
- Use these insights to:
    - Guide image model training (e.g., predict BMI or MUAC from image).
    - Select meaningful target labels.
- We can finally compare performance of structured-data ML vs. image-based CNNs later.
- Thus the AnthroVision dataset acts as a benchmark for our Deep Learning and Image Processing part of the project.

World Health Organization(WHO) Standards :

- We will use standard anthropometric z-scores used in child growth and nutrition assessment, mostly based on WHO (World Health Organization) growth standards.
- BMIz_who (BMI-for-age z-score)
    - Standardized BMI score for a child of a given age and sex, compared to a WHO reference population.
    - Assesses thinness or overweight relative to peers of the same age.
    - Interpretation :
        - $z < -2$ → Underweight or wasted ;
        - $z > +2$ → Overweight/obese
        - $z \approx 0$ → Around median of reference population
- wfa_zscore (Weight-for-age z-score) and hfa_zscore(Height-for-age z-score)
    - Standardized weight/height for a child's age and sex.
    - Detects underweight children.
    - Interpretation :
        - $z < -2$ → Underweight
        - $z < -3$ → Severely underweight

Classification Results :

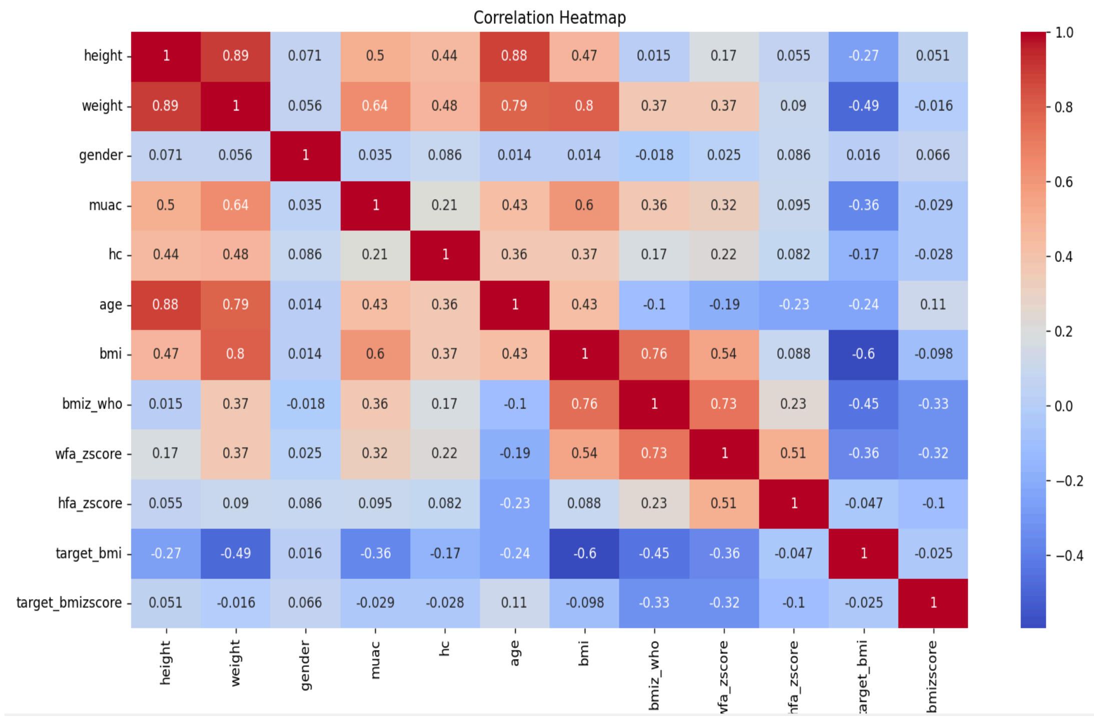




- The above graph shows that the classification of whether the child is in the malnutrition category depends on factors like :
    - age
    - weight
    - MUAC
    - height

- head circumference

- Below is the Correlation Graph between all the variables present in the dataset :



Regression Results :

- Both logistic and Random Forest Regression give similar results for the AnthroVision Dataset.
- The accuracy for the dataset in classifying the child as malnutrition is around 93% for both the models using Age , Weight , Height , MUAC , Head Circumference as the explanatory variables.

```
Logistic Regression Binary Accuracy: 0.9372384937238494
              precision    recall  f1-score   support

           0       0.94      0.97      0.96       350
           1       0.92      0.84      0.88       128

    accuracy                           0.94       478
   macro avg       0.93      0.91      0.92       478
weighted avg       0.94      0.94      0.94       478

Random Forest Binary Accuracy: 0.9309623430962343
              precision    recall  f1-score   support

           0       0.94      0.96      0.95       350
           1       0.89      0.84      0.87       128

    accuracy                           0.93       478
   macro avg       0.92      0.90      0.91       478
weighted avg       0.93      0.93      0.93       478
```

Steps Ahead :

- Through EDA, we got to know what the target anthropometric relationships look like.
- The regression models act as a baseline for anthropometric prediction (e.g., predicting BMIz or malnutrition risk) and it helps identify most predictive features.
- These insights will guide image model training (e.g., predict BMI or MUAC from image) and help us select meaningful target labels.
- Compare performance of structured-data ML vs. image-based CNNs later.
- Now using the images in the AnthroVision dataset we need to :
    - Extract both visual and anthropometric features.
    - Use deep regression models like CNN to predict Height, Weight, MUAC and Head Circumference from image features and compare with WHO growth charts
    - Use a CNN classifier to classify the child.

CONCLUSION

The project has successfully demonstrated the integration of advanced image processing and machine learning techniques for early identification of child malnutrition. The image processing pipeline, built with OpenCV and MediaPipe, enables real-time extraction of critical anthropometric features such as height, MUAC, and head circumference from both live video and static images. This system not only automates the measurement process but also ensures consistency and scalability, laying a strong foundation for large-scale screening initiatives.

On the modeling front, the use of a synthetic dataset allowed for robust experimentation with various machine learning algorithms. Exploratory data analysis confirmed that features like MUAC, weight, and height are highly predictive of nutritional status, while socio-economic indicators add valuable context for borderline cases. Addressing class imbalance with SMOTE significantly improved the recall for malnourished children, a crucial metric in public health applications. Among the models tested, XGBoost consistently outperformed others, achieving the highest accuracy, F1-score, and ROC-AUC, making it the preferred choice for deployment.

Looking ahead, the immediate priority is to operationalize the image processing pipeline on the static image dataset, calibrating pixel-based measurements to real-world units using in-image height charts. The resulting calibrated features will populate the labels.csv file, which will serve as the primary input for ongoing model training and validation. However, a key limitation remains: the absence of ground-truth labels in the current dataset prevents supervised learning on real image-derived data. Addressing this will require collaboration with field experts to annotate a subset of images, enabling direct validation and fine-tuning of the predictive models.

Future work will focus on continuous model improvement through incremental learning as more labeled data becomes available, advanced feature engineering (e.g., z-score normalization, composite indices), and the integration of explainable AI tools like SHAP for transparent decision-making. Ultimately, this project establishes a scalable, data-driven framework for malnutrition detection, with the potential to transform community health screening and intervention strategies.

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