INFORMATICS INSTITUTE OF TECHNOLOGY

In Collaboration with

UNIVERSITY OF WESTMINSTER

Automated Child Growth and Malnutrition Classification Using Image-Derived Anthropometrics and Epidemiological Data

A Project Proposal by

H.A.Janithi

Supervised by

Ms. Dilini Thamarase

September 2025

ABSTRACT

Problem: Malnutrition has remained a significant concern and still is a major concern in the world, especially in children, where it affects their development and growth. Current means of identifying malnutrition such as anthropometric measurements are usually labor-intensive and subject to human error. Also, such methods are not as efficient in distant regions with poor access to medical care. The proposed project resolves these challenges by creating an AI based solution that will be used to predictively and automatically classify the malnutrition outcome in children and provide an efficient and scalable solution.

Methodology: The malnutrition prediction in children is based on a machine learning model that is built on convolutional neural networks (CNN) and applied to the project. The system takes anthropometric measurements such as height, weight, and age and estimates the probability of stunting or wasting, according to the measurements. This information is compared to a set of benchmarks of malnutrition that are established in advance to increase the accuracy of predictions. It uses a supervised learning process to train the model, applying the relevant data on child nutrition labeled according to several datasets of this nature. The AI system will be integrated into the user-friendly application that will support real time prediction and will offer actionable information to the parent and healthcare professionals to help them make early intervention.

Initial Results: The initial model testing shows that the system can predict the outcomes of malnutrition with a high degree of accuracy and the stunting and wasting can be classified depending on the anthropometric characteristics. Real time prediction and feedback mechanisms are integrated, which enables prompt intervention and recommendation of the situation, enhancing the health of children.

Keywords: Malnutrition detection, AI driven prediction, machine learning, child nutrition, stunting, wasting, real time classification.

Contents

List of Figures

List of Tables

Abbreviations

ABSI - A Body Shape Index.

AI -Artificial Intelligence.

AUC - Area Under the Curve.

AWS - Amazon Web Services.

BRI - Body Roundness Index.

BMI - Body Mass Index.

CNN - Convolutional Neural Network.

HER - Electronic Health Record.

F1-score - F1 (harmonic mean of precision & recall).

GPU - Graphics Processing Unit.

Grad-CAM - Gradient-weighted Class Activation Mapping.

IoT - Internet of Things.

Keras - (Deep-learning library; used as a proper name).

LO - Learning Outcome

ML - Machine Learning.

OOP - Object-Oriented Programming.

OS - Operating System.

PyTorch - (Deep-learning library; used as a proper name).

ResNet - Residual Network.

RO - Research Objective.

RQ - Research Question.

SDG - Sustainable Development Goal.

Scikit-learn - (ML library; used as a proper name).

SHAP - SHapley Additive exPlanations.

SSD - Solid-State Drive.

TensorFlow - (ML framework; used as a proper name).

WH - World Health Organization.

XAI - Explainable Artificial Intelligence.

1 CHAPTER 01: INTRODUCTION

1.1 Chapter Overview

In this chapter, the foundation of the research project is presented through the introduction of the background of the problem, the definition of the problem and the motivation behind the study. It also describes the weakness of the current research, the research gap, and the contributions that this project intends to make. Moreover, the chapter addresses the main challenges, research questions, objectives and the general aim of the study. It is concluded by giving a summary to summarize the key points discussed.

1.2 Problem Background

Child malnutrition is a recognized worldwide health issue and known to be among the main causes of retarded growth, developmental delays, as well as childhood mortality. The World Health Organization (WHO), and UNICEF estimate that around 150 million children under the age of five are stunted and more than 45 million are wasting(UNICEF; World Health Organization (WHO); World Bank Group, 2025). Both short term and long term, these conditions include poor educational performance, weaker immunity, and reduced economic productivity and risk of contracting chronic diseases in later adulthood(Deng et al., 2024).

Some of the most promising methods of early detection of malnutrition are known as growth monitoring. Traditionally, to identify the nutritional status, anthropometric indices such as height-to-age (stunting) and weight/height (wasting) (Deng et al., 2024). Though weight-for-age is technically also a typical WHO indicator of underweight, in this study, the two malnutrition outcomes, namely stunting and wasting, were specifically used by the healthcare professionals. However, manual data collection and interpretation of anthropometry are generally erroneous, delay-prone, and inconsistent in most low resource settings. This leads to missed opportunities of early intervention which ultimately worsens the health outcome of the children(Rugumira, 2024).

However, recent developments in Artificial Intelligence (AI) as a field, specifically computer vision and machine learning, represents hopeful opportunities in automating the process of nutritional status identification(Santoso et al., 2025). Using image-based anthropometric prediction and predictive models that are trained on massive datasets, accelerated, more accurate, and scalable malnutrition screening can be realized. Nevertheless, in spite of the continuing developments, present systems tend to treat anthropometric data analysis or image detection separately without having integrated solutions to the problem(Alam et al., 2025).

1.3 Problem Definition

The given research is related to the development of an AI-based pipeline which is capable of estimating the anthropometric measurements (height, weight, age, and gender) of a child using an image and, subsequently, use the estimates to use them in machine learning algorithms trained on the regular anthropometric data to either classify the outcome of malnutrition in a child as stunted or wasted.

1.3.1 Problem Statement

Although a number of studies examine image-based monitoring of child growth(Reinhart et al., 2024) and other ones examine anthropometric data to classify malnutrition(Deng et al., 2024), there is no combined approach that integrates the two methodologies. This drawback leads to a decrease in the accuracy and ability to scale the malnutrition detection state, especially in low-resource settings that have few trained healthcare professionals and valid measurements.

1.4 Research motivation

This study has been prompted by the fact that child malnutrition is a serious health challenge facing the globe and therefore requires urgent solutions. Manual anthropometric measurements involve qualified human resources, and are associated with errors, which can restrict their use in resource limited areas(Rugumira, 2024). Predictive analytics together with automated image-based methods can provide a scalable, affordable, and readily available solution to ensuring that at-risk children are identified earlier(Santoso et al., 2025).

The vision of this project is to become a new tool in the hands of healthcare providers, NGOs and governments to enhance child growth monitoring initiatives by combining computer vision with nutritional data analytics. In addition to its health effect, the work also aids in the development of AI use in healthcare(Reinhart et al., 2024) and it is relevant to the Sustainable Development Goals

(SDG 2: Zero Hunger and SDG 3: Good Health and Well-being) (Santoso et al., 2025).

1.5 Existing Work

Citation	Summary	Limitation	Contribution
(Deng et al., 2024)	Constructed a nomogram model of predicting protein-energy malnutrition based on clinical and demographic variables.	Based just on defined clinical information, it is not automated.	Identifies important risk factors including gestation age, income and activity.
(Santoso et al., 2025)	Suggested nutritional status classification with explainable AI and attention-based deep learning models.	Concentrated on organized anthropometrical data.	Had a high accuracy (>99%) and model interpretability.
(Alam et al., 2025)	Proposed a hybrid AI solution (clustering + boosting) to the problem of malnutrition classification based on UNICEF data.	Needs huge, curated datasets; is not combined with image prediction	Show good stunting, wasting classification.
(Reinhart et al., 2024)	Presented a systematization of AI and child development monitoring, early detection based on image, speech and movement information.	Absence of real world tested and integrated image-based growth prediction.	Highlighted AI prospects of scalable monitoring of children and early screening of development.
(Rugumira, 2024)	Created the Mtoto Wetu Growth and Temperature	I was also based on physical	Evidence-based on the viability of digital,

	Tracking System with IoT sensors to monitor the real-time child health.	measurement instruments and human interventions; not a complete automated system.	real-time monitoring within the settings of low-resource healthcare.

Table 1: Existing Work

1.6 Research Gap

Although some of the studies have dedicated their time to automatize how malnutrition is detected between image data and anthropometric data, the existing systems are covering a single aspect of the issue. Available data like those offered by (Deng et al., 2024)and (Santoso et al., 2025) focus on tabular format results of structured anthropometric data. Conversely, other studies such as(Aanjankumar et al., 2025a) show that it is possible to utilize facial images to conduct a nutritional assessment. Nevertheless, such image-based methods are limited in diversity of datasets, and small sample sizes, as well as tend to be poorly generalized to another population. This leaves a huge disruption in the integration of both visual and anthropometric variables to predict malnutrition more precisely and smaller in scale.

Moreover, manual anthropometric measurements utilized in the conventional tests are time-consuming, prone to errors, and extremely reliant on the professional staff (Akpinar Senture and Koksal, 2025). This restricts their applicability in low resource largely rural settings where malnutrition is most common. Even though AI-based models have demonstrated high predictive accuracy, several are less interpretable and more aligned to clinical practice, and healthcare professionals have no simple solution of validating or trusting their results (Santoso et al., 2025).

The lack of a framework that would combine the prediction of the anthropometric characteristics simply based on child pictures and correlating them with structured nutrition data inspires this study. Thus, this work suggests a deep learning end-to-end pipeline model which predicts anthropometric variables (age, gender, height, and weight) based on the ARAN image dataset and integrates the estimation with Kaggle nutrition data to identify the type of malnutrition (stunting and wasting). The purpose of this methodology is to surmount the drawbacks of other models, to offer a non-invasive, scalable, and interpretable system of detecting early malnutrition.

1.7 Contribution to body of knowledge

- **Problem Domain Contribution:**
  Gives a low cost, automatic system of monitoring the growth of children with just pictures. Eliminates the use of manual measurements and human judgment in underserved rural and other under-resourced healthcare facilities(Santoso et al., 2025).
- **Research Domain Contribution:**
  Introduces a new integrated pipeline which combines image-based anthropometry with malnutrition classification restricted to stunting and wasting but has limited literature available.
  Shows how deep learning and explainable AI can be used to increase the interpretability of medical practitioners(Alam et al., 2025).
  Grows AI-powered health solutions in accordance with the world health goals.

1.8 Research Challenges

- Dataset Availability - Small annotated high-quality datasets of child images and anthropometric records.
- Models Integration - Making sure that image-based prediction and classification phases are closely connected.
- Model Generalization - Production of models that are strong in different ethnic, geographical, and socio-economic settings.

1.9 Research Question

RQ1: What is the solution to this question: how can image-based anthropometric prediction be incorporated successfully with malnutrition classification models?

RQ2: What are the main anthropometric characteristics that make a meaningful impact on malnutrition detection accuracy?

RQ3: What are explanatory methods of AI to enhance trust and utilization of malnutrition detection models in clinical settings?

1.10 Research Aim

The proposed study will focus on designing and implementing a pipeline that runs on AI, which would combine anthropometric prediction using images and anthropometric data classification to improve the early detection of child malnutrition, differentiating whether a child is stunted or wasted, and offering a scalable healthcare response.

1.11 Research Objectives

Objectives	Research Objective	Description	LOs Mapped	RQ Mapped
Problem Definition	RO1: Determine the problems in early detection of child malnutrition.	Identify flaws of traditional anthropometric solutions and explain why AI based solutions, incorporating both the prediction and classification of images, is necessary.	LO1	RQ1
Literature Review	RO2: Survey the available methods of malnutrition detection and child growth monitoring.	Compare and contrast image based methods with data based methods and name their drawbacks and show the lack of combined stunting/wasting detection models.	LO2	RQ1, RQ2
Requirement Elicitation	RO3: Find system and data requirements on creating the proposed pipeline.	Identify datasets (ARAN image dataset and Kaggle anthropometric dataset), preprocessing	LO3	RQ1, RQ2

		requirements, and ethical matters necessary to obtain an accurate stunting/wasting prediction.		
Design	RO4: Architect the integrated AI.	Design the structural dataflow and the architectural design, which integrates image-based anthropometric forecasting with stunting/wasting classification.	LO3, LO4	RQ1, RQ2
Implementation	RO5: Design the deep learning and machine learning ingredients.	Use CNN/ResNet to make anthropometric predictions and train a classifier to decide whether a child is stunted or wasted (only two possibilities).	LO4	RQ1, RQ2, RQ3
Testing Quantitative	RO6: test model performance and accuracy.	Evaluate the performance based on measures of accuracy, precision, recall, F1-score, and AUC, comparing the obtained results to the WHO standards of growth.	LO1, LO4	RQ2
Evaluation Qualitative	RO7: Assess interpretability and clinical usability.	Explainable AI (e.g. SHAP or feature importance) Test explainable AI methods (e.g. SHAP or feature importance) and get expert opinion on model	LO5	RQ3

		transparency and trustworthiness.		
Documentation	RO8: Report all development and findings.	Prepare the final report on research methodology, implementation, evaluation and conclusions.	LO5	RQ1, RQ2, RQ3

Table 2:Research Objective

1.12 Project Scope

1.12.1 In Scope

- Training of a two-stage artificial intelligence pipeline to predict anthropometric characteristics (height, weight, age, gender) and nutritional status (normal, stunted, wasted) of child images.
- Combination of the epidemiological data (age, sex, parental education, income level, feeding habit) and image-based measures in an attempt to enhance the prediction accuracy.
- Application of machine learning and deep learning engines (CNN, hybrid, attention-based networks) to perform automated classification that was in accordance with the WHO Z-score standards.
- Web dashboard design to visualize the results, tracks the growth trends, and create in-room digital reports to be consumed by healthcare workers.

1.12.2 Out Scope

- Hospital information systems integration or real-time clinical implementation.
- Other childhood illnesses other than malnutrition can be predicted.
- Creation of a mobile application (the range is confined to a responsive web application).

1.13 Hardware/Software Requirements

1.13.1 Hardware

Hardware Requirement	Justification
Intel Core i7 or higher processor	Must be able to process large datasets, deep learning models training, and real time image processing in an efficient manner
16GB RAM or higher	Facilitates the smooth running of Python-based machine learning models (TensorFlow, Keras) and eliminates memory overflow when training models.
GPU-enabled system	Offers hardware support on CNN and ResNet frameworks, cutting down on training time by a wide margin.
50GB or more SSD storage	Had to store datasets (ARAN and Kaggle), model checkpoints, preprocessed data, and output files, which can be reliably stored.

Table 3: Hardware

1.13.2 Software

Software Requirement	Justification
Operating System (Windows/Linux)	Python environments need a compatible OS and can be utilized to handle dependencies, as well as AI frameworks.
Python	Main programming language Data preprocessing, development of deep learning models, and integration.
TensorFlow / Keras / PyTorch	The fundamental deep learning frameworks to construct and train CNN and classification networks.
OpenCV	Supports preprocessing, evaluation and deployment of conventional ML classifiers.
Google Colab / Kaggle Environment	Supplies cloud GPU so that the model can be trained in a much shorter time and it does not need any kind of hardware limitation.

GitHub / Google Drive	Applied in versioning a code and backing up datasets and project management.

Table 4:Software

1.14 Chapter Summary

This chapter has identified the background of child malnutrition and defined the problem as well as the motivation of this research. The current literature and shortcomings in it were analyzed, which resulted in the definition of the gap in research. The project also provided contributions, challenges, research questions, objectives and the general aim of the project. This structure will be used to establish the basis of the subsequent chapters that will further elaborate more about the literature review, methodology, implementation, and evaluation of the proposed system.

2 CHAPTER 02: LITERATURE REVIEW

2.1 Chapter Overview

The chapter examines the literature that is available in the field of AI-based malnutrition detection, as well as image-based anthropometric prediction. It discusses the international problem of child malnutrition, constraints of the conventional growth evaluation techniques, and how artificial intelligence and computer vision are innovative solutions to precise and scalable nutritional tracking. The review addresses the problem area, the literature of the field, and technological principles, and methods of evaluation that were used in previous research. The major contributions, methodologies and limitations of the past works are also analyzed to determine the current issues in the area. A stark research gap is clear in the chapter the rest of the existing research is based on single modalities of data (image-based or clinical data) and has no multimodal integration and real-world validation. This forms the basis of the research that is proposed to create a two-step, AI based structure that incorporates image-based anthropometric estimation with clinical malnutrition classification to increase accuracy and utility.

2.2 Problem Domain

2.2.1 Overview of Child Growth and Malnutrition

Child malnutrition is an urgent problem on the global agenda where about 148 million children suffer stunting and 45 million wasting which is a symptom of chronic and acute forms of malnutrition (UNICEF; World Health Organization (WHO); World Bank Group, 2025). Conventional detection systems are based on manual anthropometric measurements, such as height and weight, that need a high-quality service and a controlled environment, preventing real-time and massive measurements, particularly in rural environments (van Dommelen, 2025). Recent improvements of AI and computer vision can provide automated solutions by processing facial and body pictures to estimate growth-related parameters (height and weight). Nevertheless, the automated image-based prediction combined with clinical malnutrition classification remains a gap, which suggests the necessity to introduce more detailed AI-based detection frameworks, including both stunting and wasting (Reinhart et al., 2024)

2.2.2 Importance of Automated Anthropometric Analysis

Anthropometric measurement plays an essential role in the identification of growth problems in children and nutrition intervention. Manual measurements are, however, not consistent particularly in distant locations. The automatic arrangements with the help of AI address these issues by capturing anthropometric features in images and allow estimating the most important growth parameters without physical interaction. Deep-learning research has demonstrated good predictability on growth characteristics of children (Aanjankumar et al., 2025b). Such systems do not just reduce the burden on healthcare workers but also provide an opportunity to monitor child nutrition continuously and on a large scale. Nevertheless, the existing AI is more predicative, and integrated systems that incorporate features of images and classifying outcomes into malnutrition should be developed to make specific diagnoses using AI such as stunting and wasting.

2.2.3 Application Areas

2.2.3.1 Clinical and Public Health Applications

Malnutrition detection systems that are based on AI will be able to revolutionize healthcare provision and general nutrition programs. Such systems can be used in hospitals and health centers to automate malnutrition by classifying children as stunted or wasted based on the WHO Z-score threshold. They are also capable of improving scrutiny in national nutrition programs and international programs through offering standardized digital evaluations(UNICEF; World Health Organization (WHO); World Bank Group, 2025). The use of AI-based automation also contributes to the task of the World Health Organization to enhance the mechanisms of early diagnosis of child growth failure. However, the current applications are not frequently incorporated in formal health care processes that are why clinically proven, AI-based diagnostic systems are in demand.

2.2.4 Challenges in Malnutrition Detection

2.2.4.1 Data Quality and Availability

The quality, quantity, and diversity of datasets that are used predetermine the reliability of AI models in identifying malnutrition. Nevertheless, the disadvantages of collecting databases of child images include the fear of privacy, labeling imbalance, and demographic bias (Deng et al., 2024). The extrapolation of findings to populations is difficult because most datasets are small-scale, region-specific or do not include clinical outcome metadata. Massive, ethically derived and demographically varied information is needed to develop models capable of classifying, stunting and wasting. The unavailability of these datasets stands in the way of the ability of AI models to generate precise and generally applicable outcomes.

2.2.4.2 Real-Time and Computational Efficiency

Very often, substantial computational resources are required to make the AI-based malnutrition detection algorithm achieve high accuracy. Though neural networks such as ResNet or hybrid deep learning networks work effectively in the laboratory, their processing capabilities render them inapplicable to the field. Consequently, AI architectures with lightweight and mobile-oriented designs are essential to ensure real-time functionality in the community health setup (Rugumira, 2024). To be used extensively, it remains a critical step to achieve the balance between accuracy and computing efficiency, which keeps being a challenging problem.

2.2.4.3 Privacy, Ethics, and Child Safety

Some of the ethical and legal concerns of using kid facial photos and biometric data are privacy, permission and storage of data. To achieve transparency and trustworthiness of AI applications to the healthcare sector, researchers emphasize that explainable AI (XAI) and responsible control of data is vital (Reinhart et al., 2024). Models should be understandable and comply with the data protection legislations to promote user acceptability and clinical reliability. Nevertheless, the lack of significant work on the application of the concept in practice is also an important aspect that should be improved, as most existing systems still focus more on technical precision than ethical standards.

2.2.5 Proposed Conceptual Architecture

To overcome these constraints of the current systems, this study suggests a two-phase AI system that integrates anthropometric estimation on images with binary malnutrition. The first stage uses convolutional neural network (CNN) model, which has been trained on image datasets of children (like ARAN), to predict anthropometric features, including height, weight, and age (Aanjankumar et al., 2025b). In the second step, a trained classification model on structured data (the Kaggle malnutrition dataset) is used to classify the nutritional status of the child as stunted or wasted, to occur based on both features that are predicted and those that are verified by the clinic(Alam et al., 2025; Santoso et al., 2025)

The method offers an interpretation-based, non-invasive and cost-effective solution, which can be deployed in a clinical or community health setting. Although a few studies have conducted research on anthropometric prediction or detection of malnutrition in general, few studies had examined a specific AI-based pipeline that classifies stunting and wasting results. The proposed research will therefore seek to fill this research gap by creating a single system that would improve the accuracy of diagnostics and scale to a variety of populations.

2.3 Existing Work

The topic of artificial intelligence (AI) and machine learning (ML) to automate malnutrition screening, growth assessment, and anthropometric prediction has been investigated in many studies. The subsections that follow summarize previous studies pertinent to this research, namely, image-based techniques, conventional anthropometric measures, IoT-based health tracking, and, finally, hybrid multimodal systems.

2.3.1 Image-Based Anthropometric Estimation

The recent developments in computer vision have facilitated automatic determination of the anthropometric features by scanning the face and body images. An experiment conducted by (Aanjankumar et al., 2025b) used a ResNet-50 deep learning model to classify and identify malnutrition using the facial characteristic and obtained a classification accuracy of 98.49%. This proved that stunting and wasting visual patterns can be efficiently pulled out using deep convolutional networks. On the same note, (Reinhart et al., 2024) conducted a systematic review of AI use in child development, with a focus on the possibility that image-based analysis could be useful in assessing growth.

Although this has been accomplished, most image-based systems are only trained on small and homogeneous datasets and do not generalize across populations. Their images are good when used in test conditions of imaging scenarios but poor in real world where there are changes in lighting, camera perspective and ethnicity. Moreover, these models give more emphasis on classification accuracy but not on computational efficiency or explanation. As such, there is still a high demand of generalized, interpretable, and resource-efficient image-based anthropometric prediction frameworks that can be used in a variety of clinical and community settings.

2.3.2 Anthropometric Indices and Growth Standards

Prior to the development of AI-based methodologies, anthropometric measures like Body Mass Index (BMI), Body Roundness Index (BRI), A Body Shape Index (ABSI) and conventional WHO growth Z-scores were used to determine malnutrition. The (Akpinar Senture and Koksal, 2025) scoping review reviewed these indices and found that although an inexpensive and an easy approach to screening, they have low accuracy in differentiating between various types of malnutrition. In addition, the accuracy of single-measure indices is usually diminished by differences in ethnicity, body structure, and age. (van Dommelen, 2025) also emphasized the weakness of using only static height-for-age records, proposing that velocity-based monitoring is more efficient in tracking the growth patterns. Although these conventional indices are also essential in comparison of the baselines, they rely on accurate manual measurement and frequent clinical follow-up. Consequently, they cannot offer prompt detection in remote regions or cases of emergencies. A combination of these indices and AI-predictive models may allow to achieve a much higher accuracy of the diagnosis, and can allow automatic and real-time monitoring, but as of now, no extensive hybrid models integrating computational intelligence and well-established anthropometric data are available.

2.3.3 Hybrid and Multimodal AI Approaches

The most recent developments in malnutrition prediction are hybrid and multimodal AI models, which integrate different learning models and sources of data. On UNICEF samples, a hybrid model was proposed consisting of Fire Hawk Optimizer (FHO) and Extreme Gradient Boosting Fuzzy (EGBF) classifier, which is cited to have over 99% accuracy in classifying nutritional status (Alam et al., 2025). Similarly, (Santoso et al., 2025) suggested CNN-LSTM framework and modified it by Multi-Head Attention and SHAP explainability, which will be more transparent and clinically reliable.

Although these hybrid systems can be more accurate than single-model architectures, they are typically limited to tabular or numerical data and are not used frequently to visual anthropometric estimation. Moreover, most of the studies are aimed at increasing the performance measures without the prior attention paid to interpretability and processing in real-time. Consequently, an obvious discrepancy still exists in terms of building an integrated multimodal architecture that would merge image-based anthropometric feature extraction with tabular clinical data classification, allowing robust, explainable, and scalable malnutrition detection in a wide variety of populations.

2.4 Technological Review

Through technical breakthroughs, computer vision, machine learning, and artificial intelligence (AI) have created a plethora of opportunities, including the development of automated systems that can predict anthropometric measures and identify malnutrition. The main technological components that underpin these systems will be discussed, including datasets and preprocessing techniques, algorithm techniques, and tools and frameworks used in model implementation.

2.4.1 Dataset and Preprocessing

2.4.1.1 Data Sources and Acquisition

The two datasets that will be used in the proposed study include ARAN dataset and a Kaggle dataset on malnutrition.

The ANR dataset is composed of images of children faces, and profiles that are associated with the anthropometric descriptions of height, weight, age and gender. This data can be used to train the convolutional neural networks (CNNs) to predict the anthropometric parameters of the visual data since it is specifically created to apply to image-based prediction (Reinhart et al., 2024). Furthermore, the dataset offers balanced samples of images with similar backgrounds and faces which are readily recognizable thus simplifying feature extraction in addition to minimizing the intricacies of preprocessing. Nevertheless, due to the fact that majority of the photos pertain to a geological area, it lacks variety in its samples and cannot be generalized to large communities.

In addition to the associated malnutrition characteristics, such as stunting and wasting, the Kaggle malnutrition dataset provides tabular clinical data, including age, gender, height, weight, and mid-upper arm circumference (Santoso et al., 2025) . In the second stage of the pipeline, which uses structured clinical packing in conjunction with anthropometric predictions from the ARAN dataset, this data is helpful for machine learning under supervision, such as classification or regression.

The combination of ARAN and Kaggle data allows implementing a multimodal strategy by applying both image-based anthropometric estimation and clinical malnutrition classification. The volume and coverage of demographic variables in the two datasets are limited, though, in that larger, ethnically varied datasets are needed for future models to generalize and apply to real-life situations.

2.4.1.2 Preprocessing Techniques

Preprocessing is essential to provide integrity and consistency to the image-based, as well as the tabular data. In the case of ARAN dataset, the image preprocessing functions include image cropping, resizing, normalization, and illumination correction to improve clarity of features and minimize visual noise (Aanjankumar et al., 2025b). Background segmentation is used to isolate facial region of the child and to reject irrelevant visual information enhancing the learning efficiency of the convolutional models. Moreover, data augmentation methods, including horizontal flipping, random rotation, and change in brightness, are applied to increase the dataset size and reduce overfitting during the model training.

Kaggle dataset preprocessing deals with missing values, outliers, and Z-score standardization of continuous variables, such as weight and height. Categorical variables such as gender are coded so that they can be used by machine learning techniques. Outlier detection enhances the reliability of the categorization outputs by ensuring that biologically implausible measures, e.g. extreme height-weight combinations, are removed (Akpinar Senture and Koksal, 2025).

Although these preprocessing techniques do improve the performance of the model, the current techniques remain dataset biased and may be prone to error or noise. The AI-based malnutrition detection systems can be made more robust and generalizable by building adaptive preprocessing pipelines that can modify themselves to variations in the image quality, illumination, and data distribution among diverse populations of children.

2.5 Benchmarking and Evaluation

The assessment of the effectiveness of AI models to detect malnutrition is not possible without an in-depth interpretation of not only quantitative indicators but also qualitative variables like interpretability, scalability, and the level of ethical reliability. This part is concerned with the main evaluation measures, comparative analyses of existing models and issues with the benchmarking of multimodal systems in combining image-based and tabular data.

2.5.1 Evaluation Metrics for Malnutrition Models

The model evaluation metrics present the quantitative basis of the ability of a system to detect malnutrition conditions using anthropometric or image data. Since the accuracy, precision, recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) are the most popular metrics. All the metrics provide another insight into the model performance and applicability to clinical use.

2.5.1.1 Accuracy, Precision, and Recall

Accuracy is the total rate of the correctly predicted results, and it is the most straightforward measure of model success. As of malnutrition classification, it measures the effectiveness of the model in separating such categories as "stunted," and "wasted”. Accuracy, however, is misleading in the case of inequality in the distribution of classes, which is typical of healthcare datasets (Aanjankumar et al., 2025b)

Precision measures what proportion of positive cases (e.g. correctly classified stunted children) of all predicted positive cases are actually positive, and recall (sensitivity) measures how many actual positive cases the model will correctly identify (Santoso et al., 2025). High recall is critical in clinical malnutrition screening since false alarms of a true malnourished case could be serious health consequences. Therefore, the tendency is to optimize the model against the trade-off between precision and recall as opposed to maximizing either of the two.

2.5.1.2 Computational Efficiency and Inference Time

In addition to accuracy, computational efficiency and inferences time are also important in determining the viability of a model to be used in the real world. Although challenges can be overcome through deep learning models, such as ResNet-50, on the ARAN dataset, these models are in general very resource-intensive and therefore cannot be deployed on any mobile or IoT device (Rugumira, 2024).

Pruning, quantization, or transfer learning can help to optimize model performance to lower the cost of computation and enable real-time malnutrition detection to be more feasible. Evaluation in this field of research therefore goes beyond correctness to runtime efficiency, scalability and resource optimality such that models are not only accurate but operationally feasible in low resource healthcare settings.

2.5.2 Comparative Analysis of Existing Models

2.5.2.1 Benchmarking Studies

The process of comparative benchmarking of existing models of AI demonstrates that the models vary considerably in the focus of methods and the outcome of performance. Studies as per (Aanjankumar et al., 2025b) with ResNet-50 have shown that image studies achieved more than 98% of classification accuracy in predicting malnutrition, indicating that the model has good visual features extraction properties. Likewise, the CNN-LM attention-based systems received similar results on clinical data, providing better interpretability and time-temporal analysis (Santoso et al., 2025).

In contrast, hybrid ensemble models such as the FHO-EGBF framework proposed by (Khan et al., 2025) achieved impressive levels of accuracy of above 99 percent on structured data at the cost of large computational time. These results indicate that even with the current maturity of AI models in terms of predictive performance, it is still limited by tradeoffs between efficiency and accuracy. The comparison also reveals a research opportunity of integrating the visual strength of CNN based anthropometric estimation and the accuracy of structured-data classifiers to generate more balanced and efficient hybrid systems.

2.5.2.2 Challenges in Benchmarking Multimodal Systems

The use of AI systems that integrate image and clinical data has distinct difficulties in benchmarking as compared to unimodal models. Evaluation is usually complicated by data heterogeneity, alignment of features and differences in normalization. In addition, compared to unified benchmarking data and measures in multimodal malnutrition detection, it is hard to compare the performance of studies (Reinhart et al., 2024).

The other dilemma is one between interpretability and predictive accuracy. Although deep networks produce better outcomes, they have an inherent limitation to clinical trust since they are black-box models. One method of explainable AI (XAI), including SHAP and Grad-CAM, is partially transparent but has not been standardized across healthcare examples. In addition, inconsistency in the reported results is due to the differences in evaluation environments, which start with laboratory simulations and going through small pilot deployments. The solution to these benchmarking inconsistencies is important in creating universally recognized evaluation standards that will guarantee accuracy and ethical responsibility of AI-based malnutrition detectors.

2.6 Chapter Summary

The chapter was a review of important studies and technologies in AI-based malnutrition detection and anthropometric prediction based on images. It emphasized the fact that even the most powerful deep learning networks like CNNs and hybrid AI systems have high accuracy; however, most current studies are confined to a single type of data and have not been proven in practice. Conventional anthropometric techniques remain common but rapid and prone to errors. It was also found that there was a lack of variety of datasets and standardized practices of evaluation in the review. Thus, the proposed study will address these shortcomings by creating a two-step multimodal AI system based on image-based anthropometric estimation with ARAN dataset and clinical malnutrition classification with Kaggle dataset.

3 CHAPTER 03: METHODOLOGY

3.1 Chapter Overview

The chapter provides the methodology of the research that will be used to design and implement the proposed malnutrition detection system based on AI and that involves image-based anthropometric prediction in combination with clinical malnutrition classification. It describes the research methodology based on the ideas of the Research Onion introduced by Saunders to determine the philosophical, strategic, and methodological framework (van Dommelen, 2025). The methodology of development shows how datasets like ARAN and Kaggle were collected, preprocessed, and modeled to predict and classify nutritional outcomes (Rugumira, 2024; Aanjankumar et al., 2025b) . The chapter also elaborates on system design, programming paradigm, testing, and solution methodology with a focus on the application of deep learning systems like CNN or ResNet to anthropometric estimation (Santoso et al., 2025). Lastly, the project management approach is presented, which encompasses the scope of the project, time frame, amount of resources needed, and the risks reduction techniques to provide a systematic development and assessment (Alam et al., 2025) . All these elements combined create a systematic framework in which the proposed research will be conducted and viable.

3.2 Research Methodology

Layer	Choise	Justification
Philosophy	Positivism	The research is conducted in a positive philosophy since data (images and anthropometric features) that will be utilized is measurable and objective and thus it is utilized to construct and test models that are consistent with scientific method (Akpinar Senture and Koksal, 2025).
Approach	Deductive	The study begins with the proven theories of malnutrition and anthropometric evaluation and validates them with the help of AI-based predictive models(Alam et al., 2025).

Methodological Choice	Mono-method Quantitative	Numerical data are analyzed by quantitative methods, including model accuracy, precision, and recall, which provide results that will be reproducible and statistically valid(Deng et al., 2024).
Strategy	Experimental	Training and testing machine-learning and deep-learning models on various datasets is done using an experimental approach to understand their performance in controlled situations(Santoso et al., 2025).
Time Horizon	Cross-sectional	The study is cross-sectional because it involves the analysis of existing data (ARAN and Kaggle) at one time, not a time prolonged(Janssen et al., 2025).
Data Collection	ARAN and Kaggle Datasets	The ARAN dataset gives the anthropometric prediction data of child images and Kaggle data contains anthropometric and malnutrition records in structured format. The two datasets have been chosen because of their relevance, completeness, and applicability to deep learning(Aanjankumar et al., 2025b).

Table 5:Research Methodology

3.3 Development methodology

The proposed system is developed through the process of iterative prototyping and pipeline (Rugumira, 2024) oriented approach that is appropriate when conducting research on machine learning. Every step in the pipeline (data collection, preprocessing, model development, integration, and evaluation) will be structured in a modular and flexible way, and it will be constantly improved.

3.3.1 Requirement Elicitation Methodology

Elicitation of requirements was done in several ways:

- **Literature Review:** Identified non-functional requirements (e.g., scalability, accuracy), as well as functional ones (e.g., feature prediction, malnutrition classification (Alam et al., 2025).
- **Dataset Analysis:** ARAN (Aanjankumar et al., 2025b) (images) and Kaggle (anthropometric + malnutrition) datasets were analyzed to establish preprocessing, feature requirements, and classification features.
- **Standards and Guidelines:** WHO (Akpinar Senture and Koksal, 2025) standards of growth were checked to verify clinical relevance.
- **Benchmarking:** An analysis of current image-based systems was conducted to determine gaps and to make the systems noninvasive and usable.

3.3.2 Design Methodology

The system design will be arranged in the form of a two-stage pipeline (Rugumira, 2024):

1. Feature Prediction Model - ARAN (Aanjankumar et al., 2025b) dataset to train CNN/ResNet models to predict age, gender, height, and weight based on images.
2. Classification Model - Kaggle data set to categorize children as normal, stunted, or wasted.
3. Integration - The first model outputs are used as inputs in the second one, which provides a flow without any stopping (Rugumira, 2024).
4. Evaluation - Models are evaluated on basis of accuracy, precision, recall, F1-score and confusion matrix.

It is a modular pipeline(Rugumira, 2024) that will provide flexibility and give an opportunity to refine each stage separately.

3.3.3 Programming Paradigm

The system uses a hybrid programming paradigm, incorporating features of an Object-Oriented Programming (OOP) paradigm in the form of modularity and reusability, and features of a functional programming paradigm in the form of data transformations and batch operations. Its core language is Python (Rugumira, 2024) , which uses the frameworks of TensorFlow, Keras, PyTorch, and Scikit-learn, both of which inherently support both paradigms.

3.3.4 Testing methodology

There are various levels of testing:

- **Model Testing:** The accuracy of each deep learning model in prediction/classification (Advancing Nutritional Status Classification, 2024) is tested.
- **Prototype Testing:** The entire pipeline(Rugumira, 2024) is tested to be operational.
- **Unit testing:** Each module is tested individually (preprocessing, prediction, classification (Alam et al., 2025)) prior to integration.
- **Evaluation Metrics:** Accuracy, precision, recall, F1-score, and confusion matrix are reliable.

3.3.5 Solution Methodology

The methodology in the solution can be summarized as:

1. **Dataset Collection:** Take samples of image data of the ARAN dataset which has images of children to predict anthropometric features and the Kaggle dataset which contains anthropometric records and malnutrition records which have been organized and classified as such(Aanjankumar et al., 2025b).
2. **Data Preprocessing:** Preprocess ARAN dataset e.g. resizes, normalize, augment data, and preprocess Kaggle data e.g. missing values, scale, and feature encoding, to maintain data uniformity and quality(Akpinar Senture and Koksal, 2025).
3. **Feature Prediction and Extraction:** Finetune neural networks like CNN or resnet to classify anthropometric features like age, gender, height, and weight using the ARAN dataset, and learn valuable features to be used in the subsequent classification step(Santoso et al., 2025).
4. **Model Selection:** Choose deep learning models to predict the anthropometric of images and the appropriate machine learning or hybrid classifiers to classify malnutrition by reference to performance accuracy and efficiency(Alam et al., 2025).
5. **Model Training:** Train sets the two models individually upon the processed datasets. The anthropometric features that are predicted by the image-based model are used to predict the attributes of a stunted or wasted child according to the classification model(Alam et al., 2025).

6. **Testing:** Assess the performance of every model based on the conventional criteria, that is, accuracy, precision, recall, F1-score, and the confusion matrix to be reliable and resistant(Deng et al., 2024).
7. **Feedback Loop:** Combine the two models into one pipeline, that is the predicted features of the image model are fed into the classification model to find out whether the child is stunted or wasted. Optimize and revise the pipeline using evaluation outcomes of the model(Rugumira, 2024).

3.4 Project Management Methodology

The project is being done by an agile-inspired iterative approach (Alam et al., 2025), which allows flexibility and improving the research.

3.4.1 Schedule

3.4.1.1 Gantt Chart

The Gantt chart can be viewed on Appendix A – Gantt chart

3.4.1.2 Deliverables

Deliverable	Due Date
Initial Project Proposal (Formative)	10th Oct 2025
Draft Project Proposal and Requirement Spec (PPRS)	24th Oct 2025
Final Project Proposal and Req. Spec (PPRS)	13th Nov 2025
Software Requirement Specification (SRS) Document	24th Oct 2025
Design Document (DSD)	15th Jan 2026
Literature Review (Draft Chapter)	31st Jan 2026
Working Prototype (for Interim Demo)	2nd Feb 2026
Interim Progress Demo (IPD) Submission	2nd Feb 2026
Completed Implementation	15th Mar 2026
Completed Testing & Evaluation Report	20th Mar 2026
Final Thesis Submission	1st Apr 2026

Minimum Viable Product (Final Version)	1st Apr 2026
Research Paper Submission	25th Apr 2026
Final Viva Voce Examination	Between 26th Apr – 10th May 2026

Table 6:Deliverables

3.4.2 Resource Requirements

3.4.2.1 Data

ARAN (Aanjankumar et al., 2025b) dataset (images), Kaggle anthropometric dataset.

3.4.2.2 Skills

Deep learning, machine learning, programming knowledge (Rugumira, 2024) and preprocessing of datasets.

3.4.3 Risk And Mitigation

Risk	**Severity**	**Frequency**	**Mitigation Strategy**
Insufficient training data	5	3	Apply data augmentation or synthetic image generation or use other datasets e.g. ARAN extensions.(Aanjankumar et al., 2025b)
Poor model accuracy	4	3	Hyperparameter Tune: Hyperparameter Tune allows users to tune the hyperparameters of their model with ease, including variations of CNNs or ResNets, and re-analyze their preprocessing pipelines(Santoso et al., 2025).
Overfitting	5	4	Use regularization, drop out layers, cross validation and enhance diversity of data set(Alam et al., 2025).
Hardware limitations	3	2	Training that is computationally intensive is done on cloud-based GPUs (Google Colab, AWS)(Rugumira, 2024).
High false-positive rate	4	3	Adjust classification levels and enhance a combination of features between the image and structured data model(Santoso et al., 2025).

Stakeholder dissatisfaction	3	2	Ensure that you are in constant contact with supervisors and domain experts; confirm requirements on a regular basis(van Dommelen, 2025).
Delays in model training	3	3	Optimize code execution, batch processing and use transfer learning with pre-trained networks(Deng et al., 2024).
Regulatory or publication delays	4	1	Get in touch with research advisors at a young age and follow the guidelines of institutional review and submission(Akpinar Senture and Koksal, 2025).

Table 7:Risk and Mitigation

3.5 Chapter Summary

The methodology of this research was described in this chapter. It used the research onion developed by Saunders(van Dommelen, 2025) to establish the philosophy, approach, and strategy and introduced the development methodology along with requirement elicitation, design, programming paradigm, testing, and solution methodology. The scope, schedule, resources and risk mitigation strategies were described using the project management methodology. Collectively, these methodological decisions form a systematic and adaptable approach to creating and validating the proposed malnutrition detection pipeline.

4 CHAPTER 04: SOFTWARE REQUIREMENT SPECIFICATION (SRS)

4.1 Chapter Summary

The chapter on Software Requirement Specification (SRS) defines the most significant functional and non-functional requirements of the AI-based Child Malnutrition Detection and Growth Monitoring Pipeline. It describes the way stakeholders (including healthcare workers, caregivers, and AI developers) were involved in the process of requirements collection, and it introduces their perspectives and illustrates their opinions and diagrams such as the Rich Picture, Stakeholder Onion Model, Context, and Use Case diagrams. The chapter also prioritizes features with the MoSCoW approach to attend to the key services, as they make the system accurate, secure, user friendly and in line with clinical and public health goals.

4.2 Rich Picture Diagram

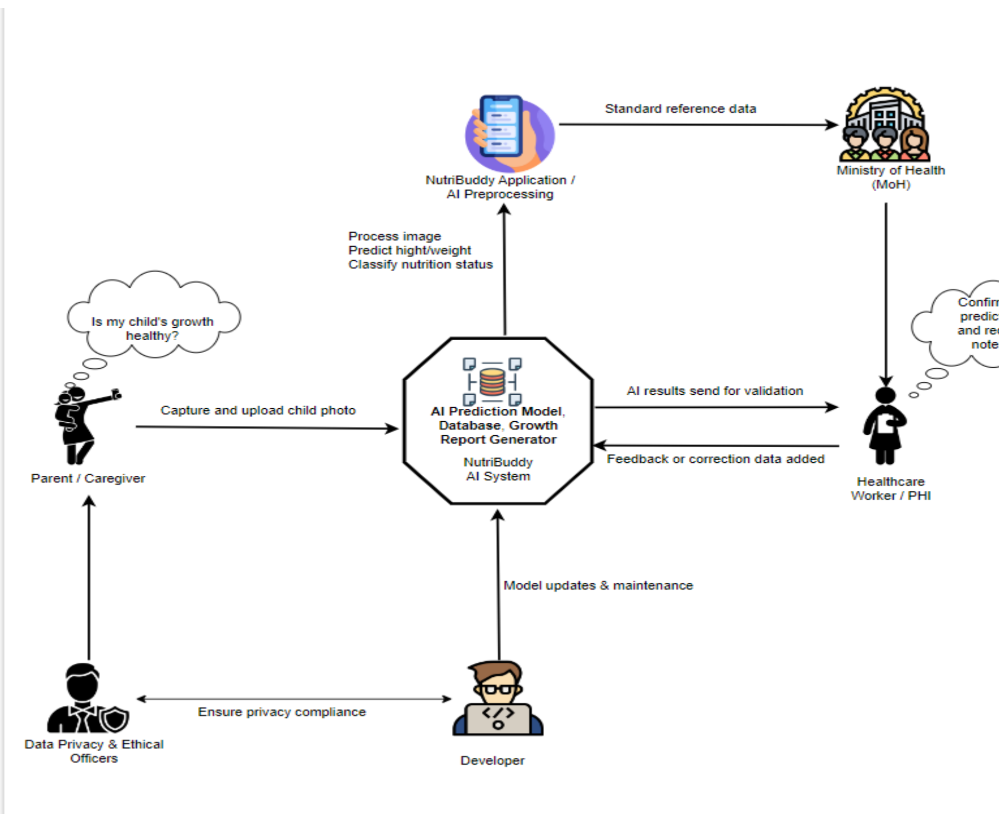


Figure 1: Rich Picture Diagram

4.3 Stakeholders Analysis

4.3.1 Stakeholder Onion Model

Figure 2:Stakeholder Onion Model

4.3.2 Stakeholder Viewpoints

Stakeholder	Viewpoints
Parents / Caregivers	Expect a simple and reliable mobile interface to capture and upload child images, receive accurate AI-based nutrition insights, and ensure the protection and privacy of their child's data.
Healthcare Workers / PHIs	Need precise and validated AI predictions, the ability to monitor child growth trends, and generate or review nutrition reports for clinical decision-making.
AI / ML Engineers	Aim to design robust and unbiased machine learning models that provide accurate anthropometric predictions and nutritional classifications.
Software Developers	Focus on building a secure, scalable, and responsive system that effectively integrates the AI components with smooth user experience.
System Administrator	Ensure consistent system performance, manage user access levels, monitor data flow, and maintain uptime and security standards.
Ethics & Data Protection Officers	Oversee user consent, ensure compliance with privacy regulations, and maintain ethical standards in data handling and AI processing.
Ministry of Health (MoH)	Utilize system-generated data to support national nutrition policies, public health planning, and child growth monitoring programs.
UNICEF / WHO	Provide international child growth and malnutrition standards to ensure global consistency and validation of AI-based nutrition assessments.
Academic Researchers	Use anonymized datasets for AI validation, model improvement, and health-related academic studies.
Hackers	Represent external security risks that highlight the importance of strong encryption, authentication, and system protection.

Table 8:Stakeholder Viewpoints

4.4 Selection of Requirement Elicitation Methodologies

Surveys: shared with community healthcare workers, parents, and carers to find out about their language preferences, user expectations, mobile device accessibility requirements, and degree of trust in AI-driven healthcare equipment. Focusing on privacy and usability features was made easier by the survey results.

Document Analysis: Consider WHO growth norms, UNICEF malnutrition data, and studies on anthropometric estimation by image and nutrition recognition systems based on AI technology. This forms a basis on which the definition of data requirements, accuracy standards, and performance measurements can be made in terms of world health standards.

Brainstorming Sessions: Collaborative discussions involving data scientists, software developers, and health officials were conducted to generate concepts for combining image-based anthropometry prediction with malnutrition classification. The real process limitations and issues with data gathering were identified through on-site observations of child health clinics.

4.5 Discussion of Finding

4.5.1 Literature Review Findings

Finding 1:
Recent research points out that machine learning and deep neural networks (including CNNs, ResNet, and hybrid attention-based systems) have a much more significant impact on enhancing the accuracy of child malnutrition prediction and automate anthropometric analysis. The malnutrition patterns can be identified by these models quite efficiently compared to the traditional clinical methods.
Citation: (Rugumira, 2024; Alam et al., 2025; van Dommelen, 2025).

Finding 2:
Although they have good model accuracy (as far as 96), most systems do not have real-world validation in low-resource clinical environments, are dataset-dependent. This limits their generalization and wider application in the countries such as Sri Lanka.
Citation:(Rugumira, 2024; Santoso et al., 2025).

Finding 3:
Research highlights the development of the idea of the increasing significance of automated growth surveillance frameworks that can be connected to national health data across child tracking. In the case of projects such as (Rugumira, 2024), it is proven that such projects are feasible but require manual inputs and do not offer AI-based feature extraction. **Citation:**(Edae et al., 2024; Rugumira, 2024).

Finding 4:
Publications which are ethical and policy-driven emphasize that privacy of their data and parental permissions required as well as explainable AI in healthcare applications using a minor as participants. The WHO (2023) and UNICEF (2025) suggest that the principles of AI ethics which uphold their transparency, fairness, and inclusivity should be followed. **Citation:** (UNICEF; World Health Organization (WHO); World Bank Group, 2025).

4.5.2 Survey Findings

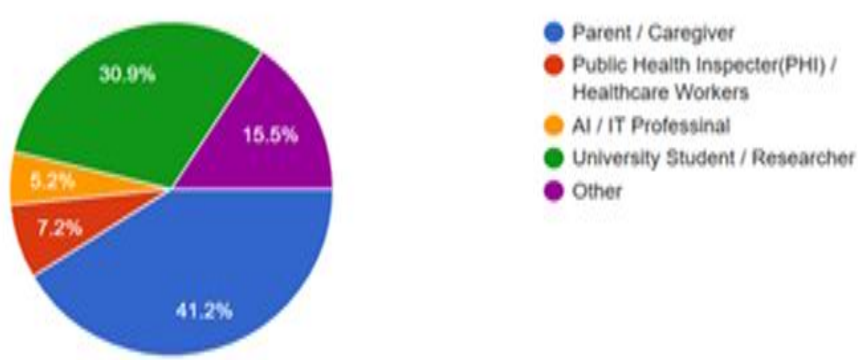
Question	What is your role?
Observations	
Conclusion	This question was aimed at assessing the diversity of the respondents and getting to know their attitude to the suggested AI-based child malnutrition detector system. It is distributed evenly, as there were parents, health officers, and researchers/technologists which were selected as the respondents to the feedback. This gives the collected insights a sense of technical feasibility and real-life applicability to the NutriBuddy project in healthcare.

Table 9:Survey Finding Question 1

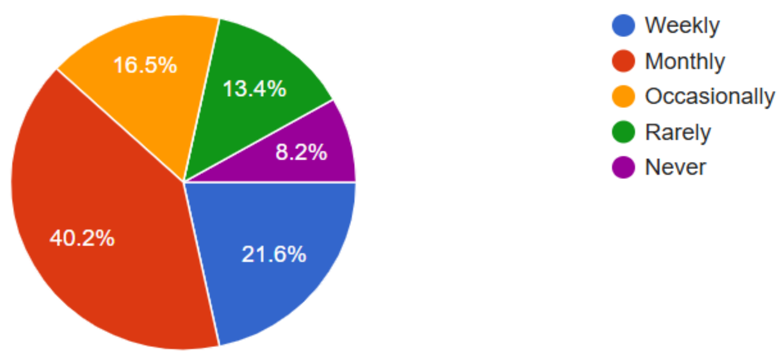
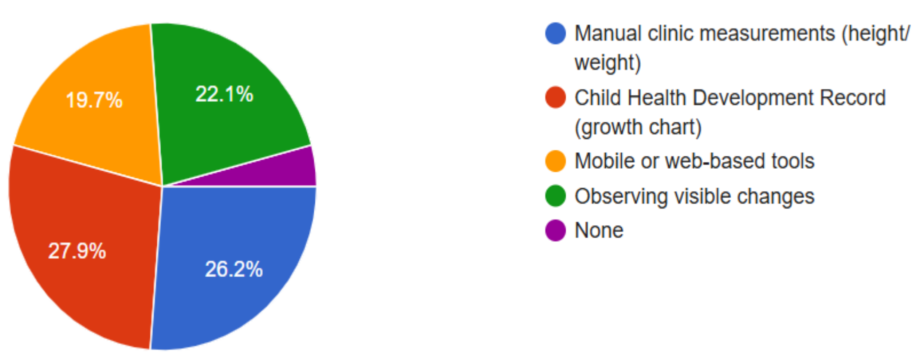
Question	How often do you monitor a child’s growth or nutrition status?
Observations	
Conclusion	The purpose of this question was to determine the frequency of monitoring child nutrition by parents and healthcare workers today. The results show that most of the families and health practitioners have a habit of regularly checking in on the family (once a week or once a month) but there is still a group who does not check regularly and only occasionally or not at all. This explains why a user-friendly, AI-based product such as NutriBuddy is necessary to promote more regular, automatic tracking and timely detect indicators of malnutrition in even non-regular trackers.

Table 10:Survey Finding Question 2

Question	Which methods do you currently use to assess a child’s nutritional status?
Observations	
Conclusion	This question was aimed at learning the practices that are already in place to test the nutritional health of children by parents and healthcare professionals. The results indicate that the traditional approaches to the analysis, such as growth

	charts and manual measurements, prevail, whereas digital tools are underused. This presents a strong option of implementing automated growth monitoring system based on AI, such as NutriBuddy, to modernize the process, deal with less manual labour and get more precise results in malnutrition detection.

Table 11:Survey Finding Question 3

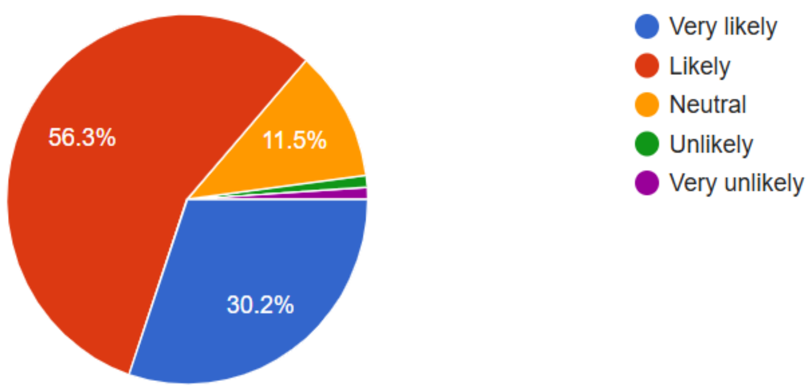
Question	If a system could analyze a child's photo and provide nutrition status, how likely would you be to use it?
Observations	
Conclusion	This question was meant to determine how users would be willing to use an AI-based solution to track child nutrition. The results indicate that most of the respondents are willing to use a photo-based AI tool, which means that the acceptance and willingness of the participants towards the NutriBuddy system is high. This supports the possibility of the system to be widely adopted by the parents and the healthcare user population.

Table 12:Survey Finding Question 4

Question	What benefits do you think an AI-based nutrition detection app could provide?

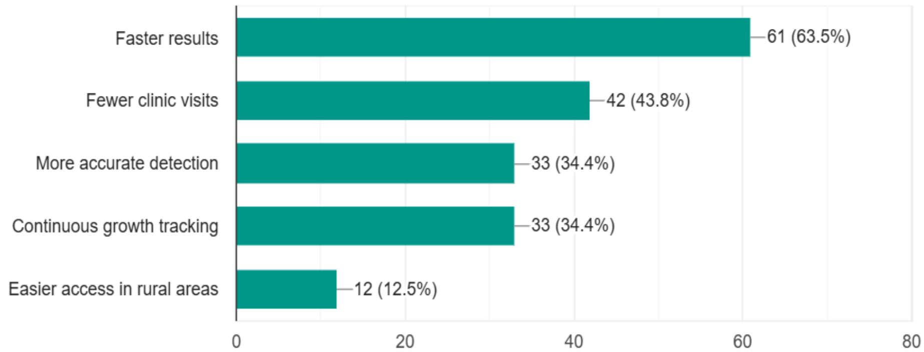
Observations	
Conclusion	This question was aimed at determining the perceived benefits of AI in the assessment of child nutrition. Findings show that users are more focused on efficiency and accessibility, and they value faster and more precise detection than manual processes. These reactions are clear indications that the design of NutriBuddy is by itself supporting the design priorities of automation, real-time prediction, and rural access.

Table 13:Survey Finding Question 5

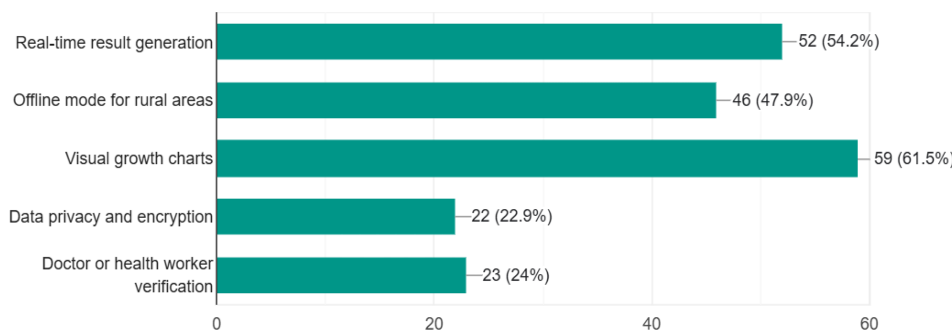
Question	Which features would you consider most important in such a system?
Observations	
Conclusion	The objective of this question was to identify the most critical system functionalities to the users. Results indicate that visual feedback and real-time feedback, along with offline access is much desired. Moreover, the participants stated that they do not disregard data protection, and secure and transparent AI-based healthcare solutions are required, which is consistent with the ethical and usability requirements of NutriBuddy.

Table 14:Survey Finding Question 6

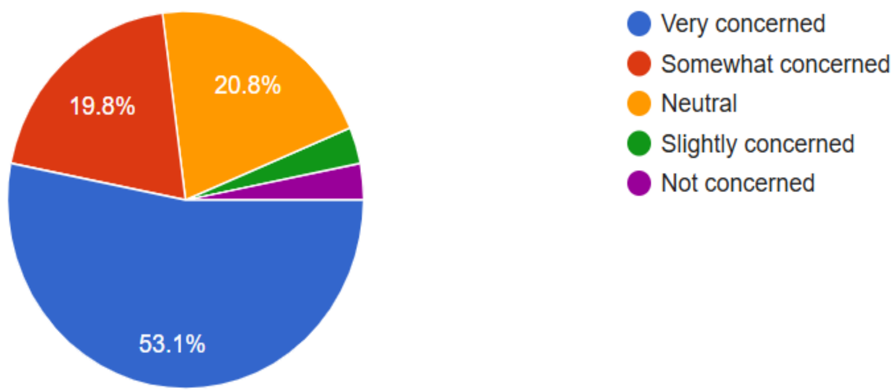
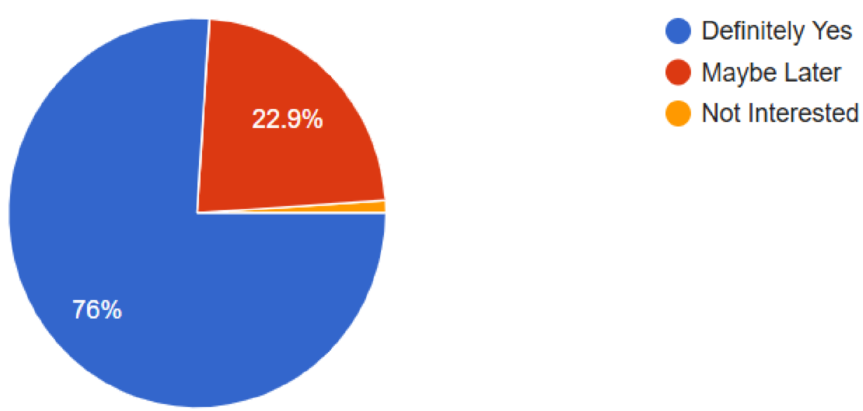
Question	How concerned are you about uploading a child's image to an AI system?
Observations	
Conclusion	This question was aimed at assessing the privacy issue surrounding image posts. The fact that the issue is very high should lead to the implementation of data encryption, user consent management, and anonymization mechanisms into the NutriBuddy system. This not only makes it conform to the Sri Lanka Data Protection Act (2022) but also makes users trust the use of AI-based healthcare applications.

Table 15:Survey Finding Question 7

Question	How concerned are you about uploading a child's image to an AI system?
Observations	
Conclusion	This question was to determine the ultimate user acceptance of the proposed solution. Findings show that there is a high level of interest and readiness to embrace NutriBuddy that proves that there is a perception among the

	stakeholders that the system is convenient, useful, and accessible. The interest rate is high, which makes the project viable and has a possibility of a real impact in the world.

Table 16:Survey Finding Question 8

4.5.3 Brainstorming/Observation

The technical design and usability of the NutriBuddy system were developed by going through brainstorming sessions and initial prototype testing with AI developers, data scientists, health practitioners and supervisors. These discussions allowed us to find the improvements of the image-processing process, real-time prediction precision, and simplicity of the user interface. It was observed that both the parents and PHI officers were fond of the clear visual growth charts and real-time feedback over complicated numerical output. The participants also stressed the presence of data encryption, anonymization, and consent to verify the adherence to the established ethical and privacy principles like the Sri Lanka Data Protection Act (2022). Overall, these meetings have helped to improve technical dependability, moral purity, and user-oriented design of NutriBuddy to be suitable both in terms of functionality and social considerations in practice in a healthcare facility.

4.6 Summary of Findings

All the required elicitation techniques were used to influence the NutriBuddy system. The literature review demonstrated that the existing AI malnutrition-detecting models are not based on real-world validation and local datasets adaptation. The interviews of the healthcare workers and parents indicated the necessity of real-time identification, automation, and data safety. The survey outcomes revealed that users were highly interested in AI-based growth tracking with such amenities as visualized responses and privacy. The workflow of the system was further narrowed down during brainstorming and emphasis was placed on ethical concerns. Selectedly, the findings confirm that NutriBuddy needs to be accurate, easy to use, and safe, ethically, to fulfill the genuine requirements of health care users and caregivers.

4.7 Context Diagram

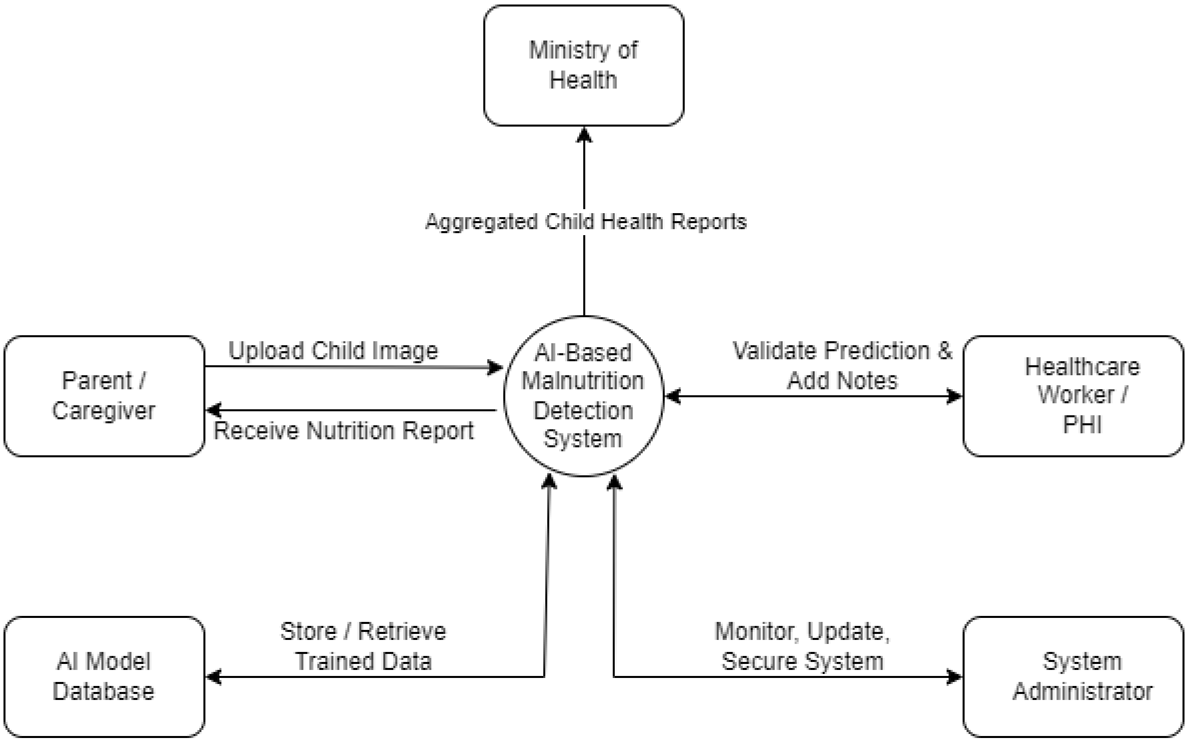


Figure 3:Context Diagram

4.8 Use Case Diagram

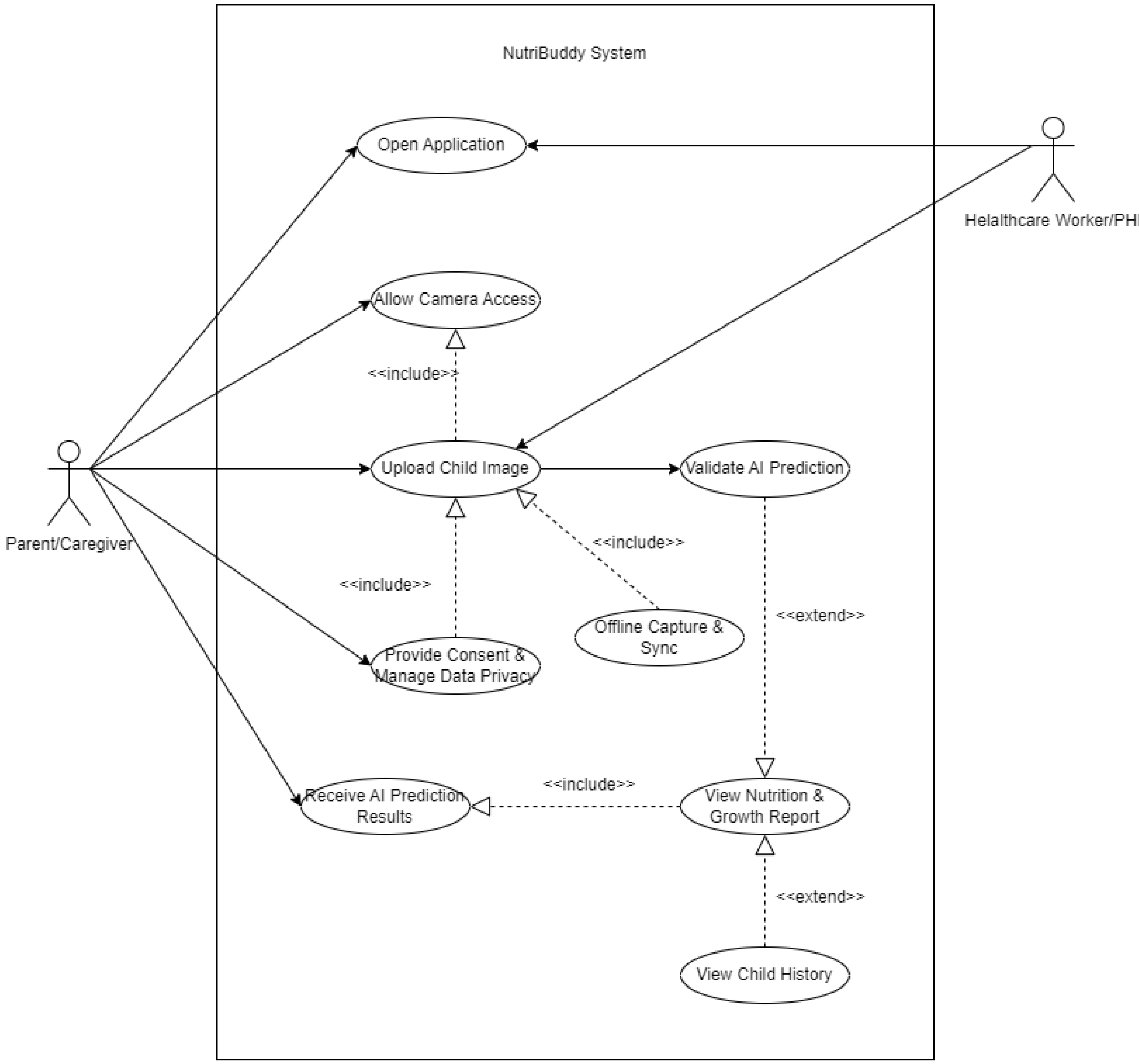


Figure 4:Use Case Diagram

4.9 Use Case Descriptions

Use Case	Description
Use Case Name	Upload Child Image
Actors	Parent/Caregiver, Healthcare Worker/PHI
Preconditions	User is logged in; camera/storage permissions are available; consent has been provided (or will be requested during flow).
Basic Flow	1. User selects Upload Image. 2. opens gallery/ camera selector system. 3. User captures/selects a clear child image and confirms. 4. System confirms file type/size and metadata (age/sex). 5. Picture is sent out to be processed.
Postconditions	Image has been sent to storage and is sent by the AI pipeline to be preprocessed.

Table 17:Use Case Description 1

Use Case	Description
Use Case Name	Receive AI Prediction Results
Actors	Parent/Caregiver, Healthcare Worker/PHI
Preconditions	A valid image has been uploaded and processed by the AI model.
Basic Flow	1. Image is preprocessed by the system and anthropometrics estimated. 2. System categorizes nutrition status based on Z-score issues of WHO 3. System notifies user and displays the result summary.
Postconditions	Predictions (metrics + status) are stored and reportable, verifiable.

Table 18:Use Case Description 2

Another Use cases can be viewed on Appendix B - Use Case Description 3 , Appendix C - Use Case Description 4 , Appendix D - Use Case Description 5 , Appendix E - Use Case Description 6

4.10 Requirements

4.10.1 Functional Requirements

ID	Requirement	Priority (MoSCoW)
FR01	The system needs to enable parents/caregivers or healthcare workers to take or post a picture of a child with the help of a mobile camera to analyze it by AI.	Must Have
FR02	Processing A processing of the uploaded image (resize, normalize) and face/body detect should take place to use anthropometric prediction with high accuracy.	Must Have
FR03	The AI model must anticipate the anthropometric variables (e.g., height, weight, age) of the processed image.	Must Have
FR04	The system should categorize the child nutritional status (Normal, Stunted, Wasted) by use of anticipated anthropometric index.	Must Have
FR05	Before submitting the reports, the healthcare worker (PHI) should be capable of validating, confirming or overruling results provided by AI.	Should Have
FR06	The system must provide and monitor an elaborate growth and nutrition report, comprised of percentile graphs and comparison over time.	Should Have
FR07	The system must enable the offline image capturing and automatic data synchronization when the internet connectivity is back.	Could Have
FR08	The system needs to ask users to consent to data usage and give privacy settings accordingly.	Must Have
FR09	There should be a multiplicity of user roles of Person of Parent/Caregiver and Healthcare Worker/PHI with various permissions.	Must Have
FR10	This should allow the users to see the past record of growth and past trend predictions by AI.	Should Have

Table 19:Functional Requirements

4.10.2 Non-Functional Requirements

ID	Requirement	Priority (MoSCoW)
NFR01	**Performance** Under ideal network conditions, the system is supposed to handle and present AI prediction output between 3-5 seconds of image uploads.	Must Have
NFR02	**Accuracy** AI model must reach an accuracy of 85-90% with regard to prediction of anthropometric parameters and nutrition classifications.	Must Have
NFR03	**Usability** It should have an easy interface, be mobile responsive and accessible by non-technical users such as the parents and PHI in rural areas.	Must Have
NFR04	**Reliability** The uptime or the system should be at least 98% to make sure that there is smooth operation of the healthcare services.	Should Have
NFR05	**Security** The system should also incorporate management of user consent and adhere to ethical policies of AI and child data protection.	Must Have

Table 20:Non-Functional Requirements

4.11 Chapter Summary

The chapter has summarized the software requirements of the NutriBuddy system capturing both functional and non-functional requirements. It explained how child's images are gathered and predicted nutritional status based on AI, and reports on growth. The system interactions were described in diagrams like Stakeholder Onion Model, use Case Diagrams, and the Context and Rich Picture. In general, this chapter outlined the key characteristics, functional objectives, and ethical standards required to make NutriBuddy precise, safe, and simple to use.

5 REFERENCE

Aanjankumar, S. et al. (2025a). Prediction of malnutrition in kids by integrating ResNet-50-based deep learning technique using facial images. *Scientific Reports*, 15, 7871. Available from https://doi.org/10.1038/s41598-025-91825-z.

Aanjankumar, S. et al. (2025b). Prediction of malnutrition in kids by integrating ResNet-50-based deep learning technique using facial images. *Scientific Reports*, 15 (1), 7871. Available from https://doi.org/10.1038/s41598-025-91825-z.

Akpinar Senture, S. and Koksal, E. (2025). Evaluating Anthropometric Indices for Malnutrition Assessment in Older Adults: Scoping Review. *Current Nutrition Reports*, 14 (1), 65. Available from https://doi.org/10.1007/s13668-025-00654-z.

Alam, Md.M. et al. (2025). Advancing Nutritional Status Classification With Hybrid Artificial Intelligence: A Novel Methodological Approach. *Brain and Behavior*, 15 (5), e70548. Available from https://doi.org/10.1002/brb3.70548.

Deng, Y. et al. (2024). Analysis and prediction of protein-energy malnutrition in children aged 8-10 years. *American Journal of Translational Research*, 16 (10), 5564–5574. Available from https://doi.org/10.62347/QIFY1619.

Edae, B.S. et al. (2024). Growth Monitoring and Promotion Service Utilization and Associated Factors Among Mothers/Caregivers of Children 0–23 Months in Sude District, Southeast Ethiopia. *Maternal & Child Nutrition*, 21 (2), e13769. Available from https://doi.org/10.1111/mcn.13769.

Janssen, S.M.W. et al. (2025). Machine learning models for predicting malnutrition in NICU patients: A comprehensive benchmarking study. *Computers in Biology and Medicine*, 192, 110326. Available from https://doi.org/10.1016/j.compbiomed.2025.110326.

Reinhart, L. et al. (2024). Artificial intelligence in child development monitoring: A systematic review on usage, outcomes and acceptance. *Intelligence-Based Medicine*, 9, 100134. Available from https://doi.org/10.1016/j.ibmed.2024.100134.

Rugumira, G. (2024). Mtoto Wetu Growth and Temperature Monitoring System for Tanzania Child Healthcare Clinics. *East African Journal of Information Technology*, 7 (1), 328–340. Available from https://doi.org/10.37284/eajit.7.1.2262.

Santoso, H.A. et al. (2025). Enhancing nutritional status prediction through attention-based deep learning and explainable AI. *Intelligence-Based Medicine*, 11, 100255. Available from https://doi.org/10.1016/j.ibmed.2025.100255.

UNICEF; World Health Organization (WHO); World Bank Group. (2025). *UNICEF/WHO/World Bank Group – Joint Child Malnutrition Estimates: 2025 Edition*. Geneva, Switzerland: World Health Organization. Available from https://iris.who.int/bitstream/handle/10665/381846/9789240112308-eng.pdf.

van Dommelen, P. (2025). The importance of height velocity in growth monitoring. *Acta Paediatrica*, 114 (1), 12–13. Available from https://doi.org/10.1111/apa.17454.

6 APPENDICES

6.1 Appendix A – Gantt chart

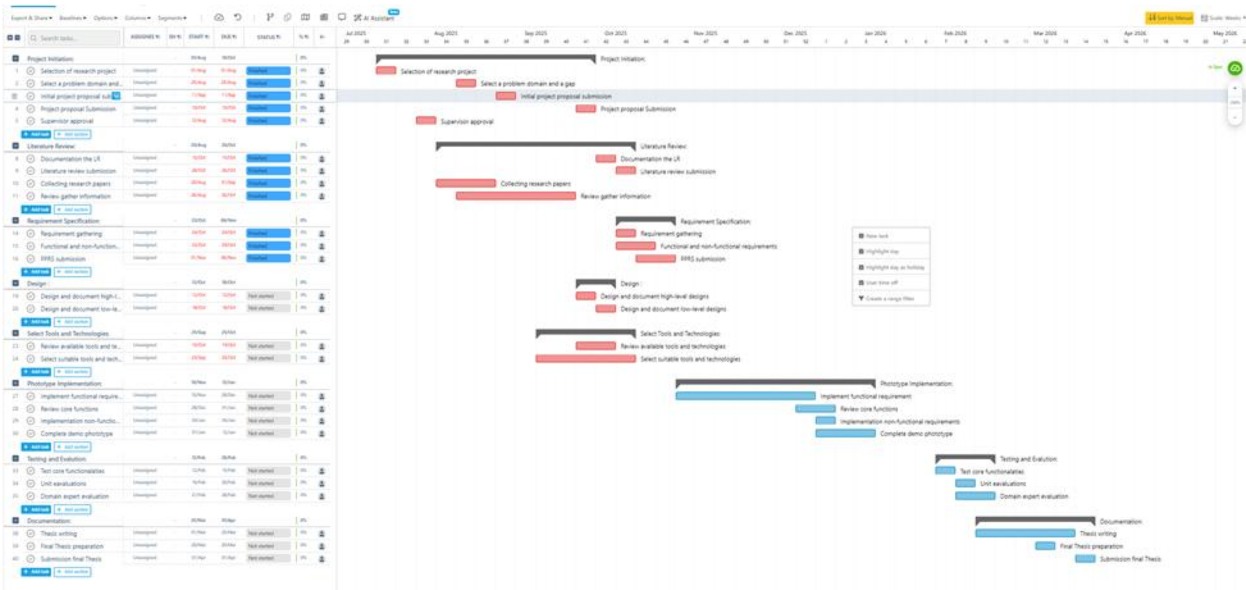


Figure 5:Gantt Chart

6.2 Appendix B - Use Case Description 3

Use Case	Description
Use Case Name	View Nutrition & Growth Report
Actors	Parent/Caregiver, Healthcare Worker/PHI
Preconditions	The results of AI-based prediction are available on the chosen child/profile.
Basic Flow	1. User opens Reports. 2. System renders nutrition status, Z-scores and charts (trends). 3. User reviews, what it recommends and follow-ups.
Postconditions	Report is available; access can be delivered as necessary.

Table 21:Use Case Description 3

6.3 Appendix C - Use Case Description 4

Use Case	Description
Use Case Name	Validate AI Prediction
Actors	Healthcare Worker/PHI
Preconditions	There is a report containing AI predictions available to the child.
Basic Flow	1. PHI opens the report and selects Validate. 2. Reviews measurements, confidence, and growth history. 3. Confirms or overrides classification; optionally adds clinical notes. 4. Saves validation outcome.
Postconditions	Final validation status and notes have been stored and can be reflected in reports/dashboards.

Table 22:Use Case Description 4

6.4 Appendix D - Use Case Description 5

Use Case	Description
Use Case Name	Provide Consent & Manage Data Privacy
Actors	Parent/Caregiver, Healthcare Worker/PHI
Preconditions	The user is authenticated; a child profile has been selected/created.
Basic Flow	1. The system presents agree statement and privacy choices. 2. user review purposes (capture, processing, storing, sharing). 3. User approves/refuses and makes preferences (retention, sharing). 4. System records time-stamped consent.
Postconditions	If consent and preferences are set; subsequent actions will respect settings.

Table 23:Use Case Description 5

6.5 Appendix E - Use Case Description 6

Use Case	Description

Use Case Name	Offline Capture & Sync
Actors	Healthcare Worker/PHI (Parent/Caregiver optionally, if app allows)
Preconditions	NutriBuddy is installed in the device; the user has registered at least once successfully; there is local storage; the network is not available or unreliable.
Basic Flow	1. Capture Offline is selected by the User. 2. Captures image and enters minimal metadata (age/sex). 3. System stores items in an encrypted local queue. 4. System auto-synch When connectivity resumes, user taps Sync, or system auto-synch.
Postconditions	Data has been uploaded; the process has been issued to server: Image and metadata are uploaded; the local queue is cleared (process statues as successful).

Table 24:Use Case Description 6