WEB-BASED NUTRITION MONITORING AND FOOD RECOMMENDATION SYSTEM FOR CHILDREN OF 1-5 YEARS IN ENUGU SATE (GrowWell)

BY

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APPROVAL

This research, titled "**Web-Based Nutrition Monitoring and Food Recommendation System for Children of 1-5 Years in Enugu State**," has been assessed and approved by the Department of Computer Science Committees in the Faculty of computing and information technology, Godfrey Okoye University, Enugu, Nigeria.

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CERTIFICATION

I certify that I completed the research included therein and that it was primarily based on my observations and investigation. Consequently, I will fully accept the University's decision if I am found to have cheated on the assignment.

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DEDICATION

This project is dedicated to God Almighty, the source of all wisdom, knowledge, and strength, whose grace sustained me through every challenge and made the completion of this project possible. And to every child in Enugu State whose health and wellbeing inspired this work, may this system contribute in some small way to a healthier and better-nourished generation.

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ABSTRACT

Child malnutrition remains a significant public health challenge among children aged 1 to 5 years in Enugu State, Nigeria, with many children suffering from stunting, wasting, and underweight conditions due to inadequate nutritional monitoring and poor dietary practices at the household level. Existing digital platforms such as RapidPro were designed for health workers and programme managers rather than caregivers, and none incorporated machine learning-based nutritional classification, locally adapted food recommendations, or structured feeding timetables using locally available Enugu State foods. This study designed and implemented GrowWell, a web-based Nutrition Monitoring and Food Recommendation System for children aged 1 to 5 years in Enugu State. The system was developed using the Object Oriented Analysis and Design (OOAD) methodology and implemented using Python, Flask, MySQL, HTML, CSS, and JavaScript. The K-Nearest Neighbors (KNN) machine learning algorithm was trained on a synthetic dataset of 1,000 child records generated using WHO Child Growth Standards (2006) to classify children's nutritional status as Normal, Underweight, Stunted, Wasted, or Severely Wasted based on Weight-for-Age (WAZ), Height-for-Age (HAZ), and Weight-for-Height (WHZ) z-scores. The system generates personalized food recommendations using twenty-eight locally available Enugu State foods and produces a structured 2-week feeding timetable tailored to each child's classified nutritional status and age group. The KNN model achieved an overall classification accuracy above 90% on the test dataset, and all fifteen functional test cases passed successfully. User acceptance testing confirmed that the system is user-friendly and locally relevant. The GrowWell system demonstrates the potential of web-based machine learning systems to improve child nutrition monitoring and dietary guidance at the household level in Enugu State, Nigeria.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Malnutrition among children under the age of five remains one of Nigeria's most important health and developmental challenges. According to UNICEF (2024), nearly one in three children in Nigeria suffers from one form of malnutrition, they are either underweight, wasting, or stunted in growth. These conditions reduce immunity, hinder growth, and affects mental and physical development in children.

In Enugu State, the situation has been worsened by economic hardship and inflation, which have significantly increased the cost of living, leaving many parents and care givers stranded and unable to provide adequate nutritious meal plans for their children. Baby formulas and processed infant have become very expensive, forcing families to rely on cheaper and less nutritious alternative.

While several meal planning programs and nutrition education exist, traditional paper-based growth monitoring used in many hospitals and clinics is also slow, outdated, and prone to human error, making it difficult to track a child's nutritional progress effectively over time. Most caregivers lack personalized guidance on how to use locally available foods, fruit and vegetables to meet their children's dietary needs.

With the growth and advancement of digital technology, web-based systems have come out as an effective tool for improving healthcare delivery and data management. Digital platforms that provides real-time monitoring, secure data storage, and easy access to information. Studies such as Sosanya *et al*. (2025) have shown that mobile and digital applications can significantly improve caregivers' knowledge of child feeding practices.

This study therefore proposes a web-based nutrition monitoring and recommendation system for children between the age of 1-5 years in Enugu State, which will be designed to help parents, caregivers, and health workers with improved nutrition tracking, providing personalized dietary recommendations, and supporting caregivers with automated nutrition advice based on age of the child and local food availability.

1.2 Statement of the Problem

Even with the efforts of government and NGOs in Nigeria, malnutrition still persists among children of 1-5 years in Enugu state due to the high cost of baby formula, economic difficulties, and limited access to reliable nutrition information.

Most parents and caregivers do not know how to create proper meal plan with an adequate nutritional value for their children using affordable and locally available foods. In addition, manual record-keeping systems in clinics and hospitals are inefficient and difficult to keep track of growth trends or provide timely advice.

Although many web-based technologies exist and have the potential to support continuous nutrition monitoring and provide personalized recommendations, there is a noticeable lack of locally adapted systems that consider regional and local food availability, and age-based nutritional requirement in Enugu state. Already existing platforms are not often not dedicated to young children or are in accessible to many caregivers due to complexity and lack of relevance to the context.

There is need for a digital, intelligent, and user-friendly system that analyzes children growth, recommend affordable nutrition options and even generate personalized feeding timetables for children of 1-5 years.

1.3 Aim and Objectives of the Study

The study aims to develop a web-based nutrition monitoring and food recommendation system for children aged 1–5 years in Enugu State, using intelligent techniques (machine learning) to support caregivers the following specific objectives were pursued:

i. analyze the existing methods of nutrition monitoring for children aged 1–5 years in Enugu State.
ii. create a web-based system that will facilitate the collection and management of nutritional data of children.
iii. develop an algorithm using machine learning techniques that will analyze the nutritional status of children.
iv. create an online food recommendation tool that takes into consideration the nutritional requirements of children.
v. This study is significant as it contributes to addressing the persistent challenge of child malnutrition, particularly among children aged 1–5 years in Enugu State and Nigeria at large.

1.4 Significance of the Study

This study is therefore important as it will help to address the problem of child malnutrition in Enugu State, Nigeria especially children within the age of 1-5. The proposed web-based nutrition monitoring and food recommendation system provide an innovative and realistic solution to improve child nutrition and health conditions.

Recent Journals, shows how internet-based technologies and intelligent techniques can be used to solve real health problems. There also serve as a proof of principle for smart, A.I.-based health care systems.

The system could improve community, population, and child-health nutrition. The system was designed for parents and caregivers to provide them with the nutrition advice that they need. This would serve as a guide to preparing healthy meals based on foods that are accessible and affordable.

1.5 Scope of the Study

It is to design and develop a web-based nutritional monitoring and food recommendation system for children (1–5) years in Enugu State.

The system would allow caregivers to enter information about the child (age, weight, height) to determine nutritional status. It would then produce individualized food suggestions and schedules based on the local food availability

The goal of this project was to develop a web-based system that takes in information about what children eat and uses that data to make nutritional analyses and recommendations.

The system employed intelligent techniques to improve the accuracy of the prescription and to analyze nutritional status.

The website isn't directly linked to hospitals, nor does it involve clinical diagnosis or medication prescription. This is meant to be an aid to caregivers, rather than a substitute for professional medical care.

1.6 Limitation of the Study

However, there are certain limitations associated with this research. The foremost of these limitations is that there is an absence of sufficient and locality-specific data sets to train the machine learning algorithm used in the study.

Secondly, the system uses information provided by the users, such as age, weight, and height. If the information is either erroneous or incomplete, there would be inaccuracies in the nutrition analysis.

Thirdly, for the success of the internet-based system, access to internet facilities is necessary along with basic digital literacy among users. It may be challenging for caregivers in rural settings or with little technology knowledge to use the system effectively.

Fourthly, due to time limitations, the system will have few functions and may miss some aspects that are relevant to child nutrition surveillance.

In addition to this, the tool is not meant to be a substitute for professional medical consultation and therefore is supposed to serve only as an additional aid for the caregiver.

1.7 Operational Definition of Terms

Malnutrition: It is a situation where the body does not have adequate levels of nutrition, which affect immunity, and physical growth.

Nutrition: This is the physiological process of the body ingesting and using food for development, energy, and body functions.

Nutrient: This refers to any component of food that the body needs to function properly, grow, and produce energy. Examples of nutrients include protein, carbohydrates, fat, vitamins, and minerals.

Child Nutrition monitoring: The process of taking measurements of the child’s height and weight at regular intervals for determining his/her nutritional status.

Nutritional Status: The state of the body of the child dependent on his/her nutrition and growth measurements.

Web-based System: A software program that is hosted by a web server and can be accessed using a browser.

Machine Learning: An aspect of artificial intelligence that allows computers to learn from information and take actions without having been explicitly programmed for doing so.

Food Recommendations: Personalized recommendation regarding the specific types of foodstuffs to be eaten by the child in light of his nutritional status.

Feeding timetable: A daily schedule indicating the types of foods to be taken by the child at every meal throughout a certain period.

Caregiver: A person who provides care to another, such as parents, guardians, and health workers who take responsibility for the nutrition and general well-being of a child.

Locally Available Foods: Food products that are cultivated and consumed locally.

Digital Technology: Tools, systems, or platforms used to process, store, and transmit information electronically.

Underweight: A nutrition-related condition whereby the weight of a child is significantly lower than what it should be for his/her age and gender.

Stunting: A condition resulting from poor nutrition wherein the child is significantly shorter than expected for his or her age and sex.

Wasting: A condition caused by poor nutrition whereby the child is significantly lighter than expected based on height.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter summarizes the existing literature on malnutrition, child nutrition monitoring, and application of digital technologies to nutrition challenges. The literature highlights limitations of prior studies, as well as their contributions. This therefore forms the basis for the need for a web-based nutrition monitoring and food recommendation system for children within the age brackets of 1 to 5years in Enugu State.

2.2 Theoretical Background

This section provides the basic concepts and theoretical background of the study. Concepts regarding child nutrition, malnutrition, nutrition monitoring, web-based systems, and machine learning in healthcare and nutrition are expounded.

The theoretical background deals with the fundamental concepts and ideas that forms the foundation of the design and development of the proposed system. Specifically in this study, the theoretical background brings out how these concepts relate to the eradication of the problem of malnutrition among children aged 1 – 5 years in Enugu State and Nigeria in general.

We consider these concepts to provide a framework for the successful incorporation of digital technologies and A.I. into the food recommendation and nutrition tracking space

2.2.1 Child Nutrition and Growth

In the first five years of life, nutrition is critical to mental and physical development. Nutrients fuel the growth of the body and the brain and strengthen the immune system. Poor nutrition during this period can lead to stunting, diminished cognitive potential and downstream health issues.

2.2.2 Malnutrition in Children

While malnutrition can also refer to excess consumption of nutritionally empty foods, when it comes to children it most often means undernutrition. Undernourished children are underweight for their age, wasted (underweight for their height) or stunted (abnormally short for their age). In developing countries such as Nigeria, the causes of malnutrition are rooted in poverty, poor feeding practices and lack of access to health care.

2.2.3 Nutrition Monitoring Systems

Nutrition monitoring is the ongoing tracking and assessment of a child's growth, using age, weight and height as markers. In the past, and even today, nutrition monitoring systems have been mostly manual and paper-based. The use of digital systems can at least enhance access, storage and tracking of nutritional status.

2.2.4 Web-Based Health Systems

Web-based systems are applications that users access via internet browsers to enter, store, and recall information. In healthcare, these systems are cutting errors, improving data management and service, and providing data remotely.

2.2.5 Machine Learning in Healthcare

Machine learning is a subset of AI focused on the ability for systems to learn from data in order to make decisions or predictions. In health care, we see machine learning systems begin to be used for diagnosis, prediction and recommendation systems. The study results suggest that ChatGPT can be used in nutrition surveillance to analyze data from children and provide tailored diet plans to them.

2.3 Review of Related Works

A number of studies have examined the problem of malnutrition, particularly in developing countries like Nigeria.

Tuffrey *et al*. (2021), who developed an S.M.S.-based digital outscale program for monitoring severe acute malnutrition in northern Nigeria. The system was designed to improve the timeliness and efficiency of data reporting in nutrition programmes. The system showed that digital tools can improve upon antiquated, paper-based methods for improving monitoring processes, but was limited to data reporting, not hands-on support of caregivers.

Sosanya *et al*.(2025) designed a mobile-based application to improve mothers' knowledge of infant and young child feeding practices in Nigeria. The app contained educational material and suggested appropriate feeding strategies, but did not have automated food recommendation features. The team found that the use of mobile apps meaningfully increased the users' nutrition knowledge.

A study by Egwudo *et al*. (2025) on the use of digital health technologies within the healthcare system in Nigeria.

While the study elucidates the importance of digital systems in improving healthcare delivery, data management, and access to services, it does not propose a system for generating personalized dietary recommendations or nutrition monitoring of children. It prescribed no new system for producing personalized dietary recommendations and was not focused specifically on children.

In 2025, Bailey and Okoduwa evaluated social media as a platform for public health nutrition in low and middle-income countries. Their study highlighted the ability of technology to provide nutrition information and encourage healthy eating.

But the approach they studied focuses only on awareness and not on monitoring nutritional status or providing personalized recommendations.

Ojo *et al*. (2025) examined the use of artificial intelligence in nutrition education systems. We found that A.I.-driven platforms can provide individualized learning experiences in alignment with established guidelines and improve user engagement. But our work was mostly theoretical; we didn't build a working system or develop one specifically for children or for Enugu State.

In a 2024 study, Obasohan *et al.* investigated socioeconomic determinants of child malnutrition in Nigeria. They found poverty, maternal lack of education and inability to access health care to be the main predictors of malnutrition. The study doesn't address how technology might tackle malnutrition.

Adebayo *et al.*(2020) showed poor feeding and dietary practices further contributed to the high levels of malnutrition. And, critically, the study didn't suggest the use of any digital system to improve nutrition monitoring or feeding practices.

Ibeawuchi *et al.* (2017) assessed the nutritional status of children in rural Nigeria and found a high prevalence of undernutrition due to poor access to nutritious foods and limited health services. Although the study highlighted the severity of the problem, it did not provide a technological solution or system to address these challenges.

A 2021 paper in the journal IEEE Access described machine learning-based diet recommendation system that uses algorithms to give personalized dietary advice. That system, however, was not designed for children, nor did it incorporate the local food landscape in Nigeria.

Now, that result is not particularly realistic. While this system demonstrated the potential of A.I. in improving nutrition management, it was not localized or tailored to the needs of children aged

1-5 years in Enugu State. In this study, we develop an A.I.-embedded nutrition advisory system for children ages 1-5 years.

Similarly, a machine learning-based nutrition monitoring system (2023) proposed the use of intelligent algorithms to predict nutritional status and support decision-making.

2.4 Summary of Literature Review

S/N	AUTHOR(S)	CONTRIBUTIONS	METHODOLOGY	LIMITATIONS
1	Tuffrey *et al*. (2021)	Developed SMS-based malnutrition monitoring system	SMS-based digital reporting (RapidPro)	No caregiver interaction or personalized recommendations
2	Sosanya *et al*. (2025)	Mobile app for nutrition	Mobile application (experimental study)	No nutrition monitoring or prediction
3	Egwudo *et al*. (2025)	Digital health integration in Nigeria	Systematic review of digital health systems	Not nutrition-specific and no system design
4	Bailey & Okoduwa (2025)	Social media for nutrition awareness	Literature review / communication model	No tracking, monitoring, or personalization
5	Ojo *et al*. (2025)	AI-based nutrition education system	Conceptual AI model / theoretical approach	No real-world implementation
6	Obasohan *et al*. (2024)	Identified causes of malnutrition	Statistical analysis (survey data)	No digital or technical solution proposed
7	Adebayo *et al*. (2020)	Studied feeding practices	Field survey and observational study	No system or intervention developed
8	Ibeawuchi *et al*. (2017)	Rural nutrition assessment	Cross-sectional study	No technological approach
9	IEEE Study (2021)	ML-based diet recommendation system	Machine learning (classification/recommendation algorithm)	Not child-specific or localized to Nigeria
10	ML Study (2023)	AI-based nutrition monitoring system	Machine learning predictive model	Not adapted to Nigerian context or local foods

2.5 Research Gap

Furthermore, to the best of our knowledge, there is currently no single web-based application that combines classification of nutritional status and personalized food recommendation based on locally available foods and a well-structured two weeks feeding time table and recipes of family foods that can be accessed directly by caregivers. None used machine learning to analyze nutritional data or included a locally adapted food database for use in Enugu State, and most were designed for use by health workers, rather than caregivers. The GrowWell Nutrition Monitoring and Food Recommendation System was therefore developed to fill these gaps.

CHAPTER THREE

SYSTEM ANALYSIS AND DESIGN

3.0 Introduction

This chapter presents a detailed analysis and design of the GrowWell Nutrition Monitoring and Food Recommendation System for children aged 1 to 5 years in Enugu State. The Object Oriented Analysis and Design (OOAD) methodology was adopted for the development of this system. This chapter covers the analysis of the existing system (RapidPro) and its identified limitations, the objectives of the proposed GrowWell system, the system requirements specification, the OOAD methodology and its justification, UML diagrams(Use Case Diagram, Class Diagram, and Activity diagram), and the system design including input design, output design, database design, and system architecture design.

3.1 Analysis of the Existing System

System analysis is the process of examining an existing system to understand how it works, identify its strengths and weaknesses, and determine the requirements of a new or improved system. In this study, RapidPro was identified and analyzed as the existing system used for child nutrition data collection and reporting in Nigeria.

3.1.1 Overview of RapidPro

In Nigeria, NGOs and health organizations have used RapidPro, an open-source digital platform developed by UNICEF, to monitor child nutrition. The platform allows organizations to build and connect messaging workflows that can work through SMS, social messaging channels and voice calls. Community health workers community groups can use the platform to gather and report back child growth data to central databases. The need to address malnutrition in developing countries at the community as well as clinical levels was first highlighted by Muller and Krawinkel in 2005. Two digital platforms that have been used most widely in the delivery of nutrition programmes are RapidPro (previously known as RapidSMS) and CommCare. For example, the use of RapidPro improved timeliness and efficiency of severe acute malnutrition data reporting for nutrition programmes in Northern Nigeria (Tuffrey et al.

RapidPro is not meant to be used primarily by regular caregivers, but by trained community health workers. As Black et al. (2013) notes, child nutrition interventions must reach caregivers directly at the household and community levels if they are to achieve real impact in reducing rates of undernutrition. As noted by Egwudo et al. (2025) noted that digital health platforms have the potential to improve data management and how health care is delivered.

3.1.2 Limitations of the Existing System (RapidPro)

Despite its contributions to improving data reporting efficiency in nutrition programmes, the following limitations were identified in RapidPro that justify the need for the proposed GrowWell system:

i. The system is solely geared toward collecting and transmitting the data to programme managers (Tuffrey et al., 2021). RapidPro does not produce any personalized dietary advice for the parent or caregiver of the child.

ii. it does not generate a meal plan or feeding schedule for your child. RapidPro is a data transmission and workflow automation service and does not have any features for generating individualized nutrition plans that integrate locally available foods.

iii. RapidPro's A.I. simply receives the raw growth information. The RapidPro system doesn't automatically apply the W.H.O.'s growth standards to interpret the results. Ojo et al. (2025). The integration of A.I. and M.L. into nutrition systems improves the quality and personalization of nutritional advice.

iv. It also is not designed for a caregiver but for an educated health worker who can be trained to use the system, and for program managers. But RapidPro cannot be used by parents or guardians independently to track a child's development at home or to get nutrition counseling (Sosanya et al., 2025).

v. RapidPro does not contain a locally adapted food database. It does not take into account locally available foods in Enugu State, such as ugwu, abacha, okpa, ofe onugbu, or akamu na akara. Recent studies have highlighted the need for greater contextualization of nutrition systems, particularly in low- and middle-income settings, with data demonstrating the critical role of diet quality for health outcomes (Bailey & Okoduwa, 2025).

vi. SMS lacks the richness and volume of data that can be captured through a platform. Getting on the scale is not quite so simple. The platform relies on SMS messaging for data input, which is limited in terms of the richness and volume of data that can be captured.

vii. RapidPro doesn't provide individual caregivers with a dashboard or view of the child's growth history. Programme managers, at the organizational level, are able to view the historic records and graphical representation of growth trends, but such data is not available to caregivers.

3.1.3 Analysis of the Proposed System (GrowWell)

The proposed GrowWell Nutrition Monitoring and Food Recommendation System is a web-based application designed to help caregivers monitor the growth of children aged 1–5 years in Enugu State. The system allows caregivers to register, log in, add child profiles, record growth measurements, receive personalized food recommendations, view a two-week feeding timetable, and track growth history.

The system also provides an administrative module for managing caregivers, food categories, food records, children's records, and system reports. By providing locally relevant food recommendations and maintaining child growth records, the proposed system offers a more user-friendly and practical solution for improving child nutrition monitoring than the existing system.

3.2 System Requirements Specification

The System Requirements Specification (SRS) defines what the GrowWell system is expected to do and the quality standards it must meet. Requirements are classified into functional requirements and non-functional requirements.

3.2.1 Functional Requirements

i. Caregivers must be able to sign up for a new account using name, phone number, email, LGA and a password.
ii. Registered caregivers shall have a secure log in and password.
iii. The system shall allow caregivers to add multiple child profiles, with each profile containing the child’s full name, date of birth, and gender.
iv. The system should automatically calculate a child’s current age in months based on date of birth at the time of each analysis.
v. Caregivers should be able to enter weight in kilograms and height in centimeters.
vi. The system shall calculate Weight-for-Height Z-score (WHZ), Weight-for-Age Z-score (WAZ), and Height-for-Age Z-score (HAZ) based on the 2006 WHO Child Growth Standards.
vii. The KNN machine learning model is also used to classify the child’s nutritional status based on the z-scores.

viii. It will also display individualized nutritional counseling information based on dietary needs with locally available foods from Enugu State.

ix. The system will produce and display a feeding schedule for a 2-week period (14 days), showing breakfast, morning snack, lunch, and dinner for each day.

x. The system will store all growth records.

xi. The system should have a dashboard that shows all children registered in the system with their most recent nutritional status.

xii. For each child, the system shall provide an overview of all past information for that child so that the caregiver can see a child's complete growth history, including all past records, previous z-scores, and older schedules.

xiii. Caregivers can print and/or save the feeding schedule.

3.2.2 Non-Functional Requirements

i. Usability: The system interface must also be simple enough to be used easily by caregivers with a basic level of digital literacy. Sosanya et al. (2025

ii. Performance: The system will be able to process child data and run the KNN analysis (Cover & Hart, 1967) with a reasonable response time when connected to a local server.

iii. Security: Caregiver passwords must be stored as secure, hashed values. User sessions must also be managed securely to ensure that child records cannot be accessed by an unauthorized user.

iv. Reliability: The system should always return the correct anthropometric status classifications according to the WHO z-score thresholds (WHO, 2010) as well as the correct food recommendations for each anthropometric status.

v. Scalability: The system should be capable of handling multiple caregivers and multiple children without a performance penalty.

vi. Maintainability: The code will be divided into modules so it can be easily modified.

vii. Compatibility: The system must work properly on typical web browsers (e.g., Google Chrome, Firefox, and Microsoft Edge).

3.3 System Design Methodology

In developing the GrowWell system, the Object Oriented Analysis and Design (OOAD) methodology was adopted. OOAD is a methodology used in software engineering in which a system is modeled as a group of interacting objects, with each object representing an instance of a class. OOAD is a combination of two disciplines: Object Oriented Analysis (OOA), which is concerned with understanding and defining the problem, and Object Oriented Design (OOD), which is concerned with designing a solution. They must be systematically documented, systematically designed and use a structured methodology such as OOAD WHO (2021)

3.3.1 Justification for OOAD

i. The GrowWell system deals with a number of real-world entities, such as Caregivers, Children, Foods, Growth Records, Feeding Timetables, Food Recommendations, and Nutritional Status, and so naturally lends itself to an object-oriented approach. Each of these entities has well-defined characteristics and behaviors, and each can be naturally modeled directly as a class.

ii. The primary advantage to OOAD is that it promotes modularity and reusability, making the system easier to maintain and extend later. The IEEE Study (2021) demonstrated that object-oriented design principles improve the maintainability and scalability of machine learning-based recommendation systems.

iii. OOAD makes use of UML diagrams. The Activity Diagram, Use Case Diagram, and Class Diagram generated in this study served as a complete blueprint in the successful implementation of the GrowWell system.

iv. In this study, it uses the Python programming language to implement the Flask back end and a KNN (K Nearest Neighbour) machine learning model (Cover & Hart, 1967) whose object-oriented nature lends naturally to the application of OOAD [object-oriented analysis and design] methodology.

v. In Nigeria university system, OOAD is used to evaluate final year project and is the most suitable academic choice for a web-based system project.

3.3.2 Method of Data Collection

Data for this study came from two main sources. As a reference data set for generating synthetic training data for the KNN model, we used the World Health Organization's (WHO) Child Growth Standards (WHO, 2006). The WHO Child Growth Standards provide the median weight and height by sex and age, as well as the standard deviations. We used this data to calculate z-scores and generate 1,000 artificial children representing the different categories of nutrition. In Black et al. (2013) the best way to identify malnutrition in children under 5 is to use an index known as a z-score based on W.H.O. The z-score classification cutoffs are based on the WHO

(2010) Nutrition Landscape Information System, where a z-score of <-2 is considered moderately malnourished, and a z-score of <-3 is considered severely malnourished.

Second, the food composition data and feeding guidelines used in the food recommendation and timetable modules were sourced from the UNICEF Infant and Young Child Feeding guidelines (UNICEF, 2021) and the FAO/WHO West African Food Composition Tables (FAO & WHO, 2012). These provided the nutritional values for locally available Enugu State foods such as ugwu, abacha, ji, akamu, ofe onugbu, ofe egusi, okpa, ukwa, and crayfish.

3.4 Object Oriented Analysis (OOA)

Object Oriented Analysis involves identifying the key objects in the system, defining their attributes and behaviors, and establishing the relationships between them. The following objects were identified in the GrowWell system through analysis of the system requirements.

3.4.1 Identification of Objects and Classes

Table 3.1: Identified Classes, Attributes and Methods

Class	Key Attributes	Key Methods
Caregiver	id, full_name, email, phone, password_hash, lga	register(), login(), logout(), addChild()
Child	id, caregiver_id, full_name, date_of_birth, gender	calculateAge(), addGrowthRecord(), viewHistory()
GrowthRecord	id, child_id, weight_kg, height_cm, age_months, recorded_at	save(), calculateZScores()
NutritionalStatus	id, growth_record_id, waz, haz, whz, status_class, ml_summary	classify(), getRecommendations(), generateTimetable()
Food	id, category_id, name, local_name, protein_g, carbs_g, fat_g, iron_mg, zinc_mg, vitamin_a_mcg	getByCategory(), getByAgeRange()
FoodCategory	id, name, description	getFoods()
FoodRecommendation	id, status_id, food_id, priority_level, reason	generate(), display()
FeedingTimetable	id, status_id, start_date, end_date, duration_weeks	generate(), print()
TimetableMeal	id, timetable_id, food_id, meal_name, day_number, meal_type, preparation_tip	getByDay(), getByMealType()
KNNModel	k, metric, model_path, scaler_path	load(), analyze(), scaleInput()

3.4.2 Relationships between Classes

i. Association (One-to-Many): A Caregiver can register and monitor many Children. Each Child belongs to exactly one Caregiver.

ii. Association (One-to-Many): A Child can have many GrowthRecords taken over time. Each GrowthRecord belongs to exactly one Child.

iii. Association (One-to-One): Each GrowthRecord is linked to exactly one NutritionalStatus object, which stores the z-scores and KNN classification result (Cover & Hart, 1967).

iv. Association (One-to-Many): A NutritionalStatus result is linked to many FoodRecommendations, as multiple foods are recommended based on the classified status.

v. For each NutritionalStatus result, one FeedingTimetable is produced, with a 14 day meal plan.

vi. A FeedingTimetable consists of multiple TimetableMeal objects (a One-to-Many composition), each of which details one meal on one day of the plan.

vii. This is a Many-to-One relationship, a FoodCategory contains many Foods, but a Food belongs to one FoodCategory.

3.5 Object Oriented Design (OOD)

Object Oriented Design. Transform the objects and relationships identified during the analysis into design.

3.5.1 Use Case Diagram

The Use Case Diagram (Figure 2) describes the interactions of the two main actors (Caregiver and Admin) and the main functions of the system. Nine use cases are included through which the Caregiver interacts with the system. These use cases are Register Account, Login, Add Child Profile, Enter Growth Measurements, View Food Recommendations, View 2-Week Feeding

Timetable, View Growth History, Analyze Nutritional Status, and Logout. The Admin interacts with the system through five use cases: Manage Caregivers, Manage Foods Databases, See All Children Records/Generate System Reports and Manage Food Categories.

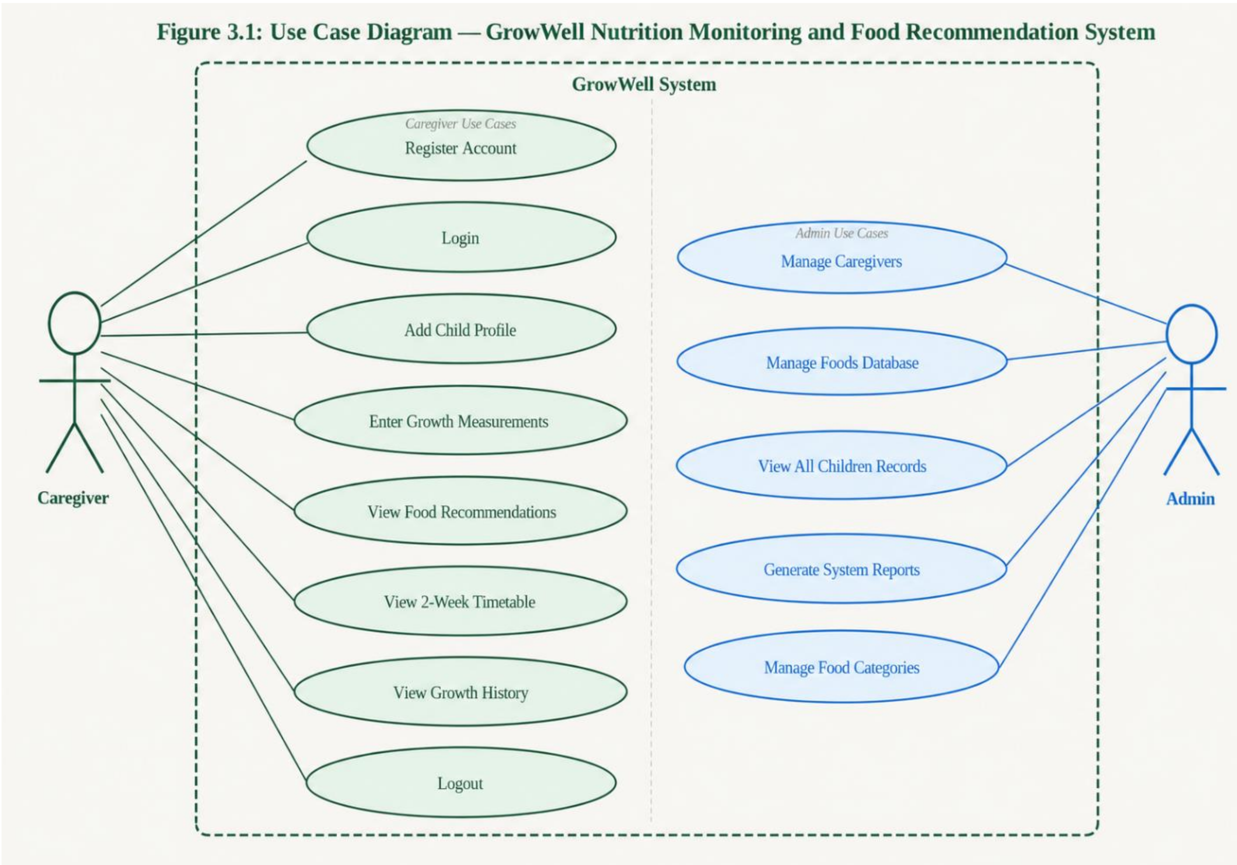

Figure 3.1: Use Case Diagram — GrowWell Nutrition Monitoring and Food Recommendation System

3.5.2 Class Diagram

The Class Diagram in Figure 7 shows all the classes that were identified in the Object Oriented Analysis. This diagram consists of ten classes, whose attributes, methods, and relationships correspond to the nine-table relational database implemented in MySQL. The class structure of KNNModel is consistent with the object-oriented design approach described by the ML Study

(2023) regarding intelligent health monitoring systems. Moreover, it reflects the nearest neighbor classification algorithm originally described by Cover and Hart (1967), but implemented with the scikit-learn library in Python.

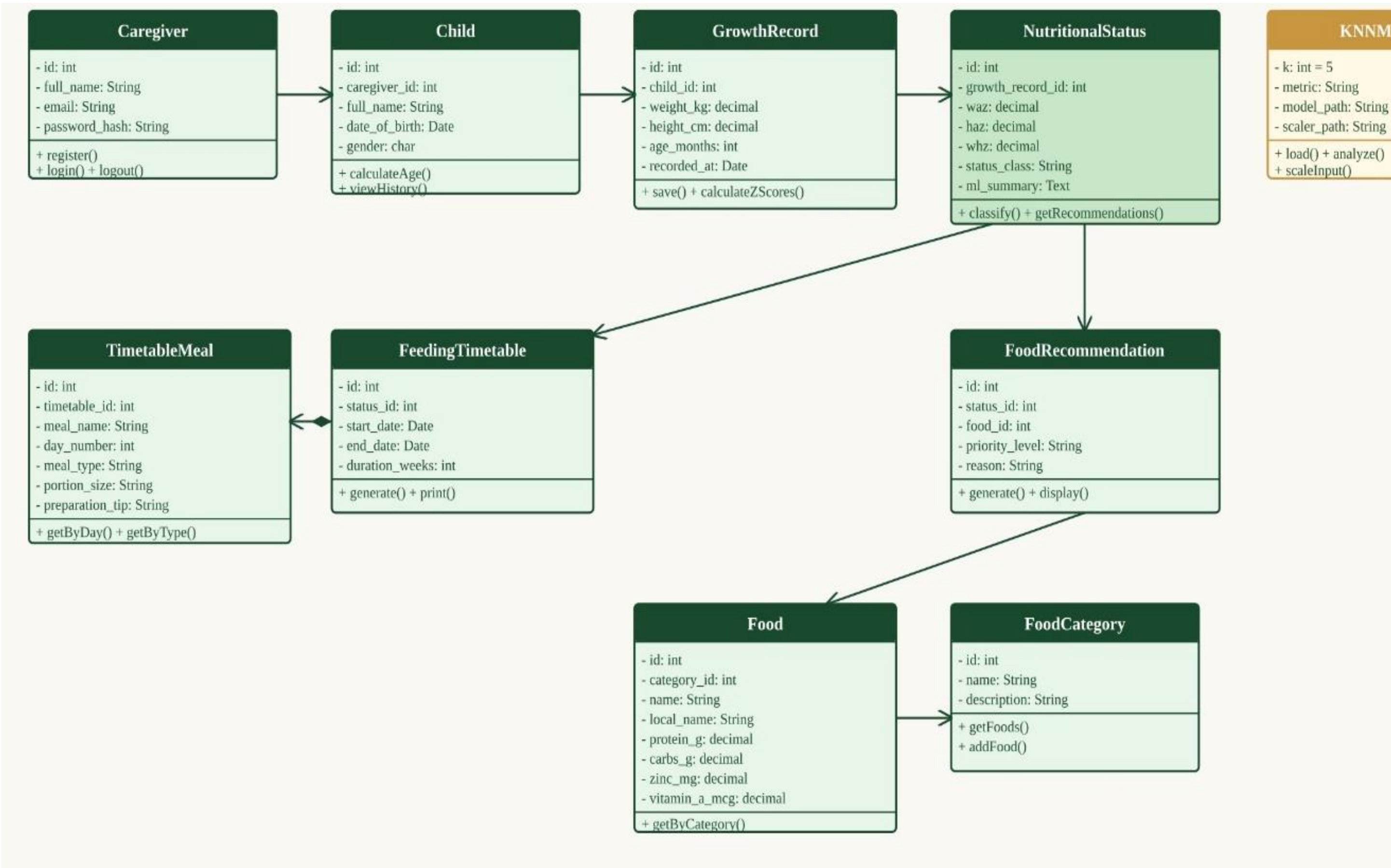

Figure 3.2: Class Diagram — GrowWell Nutrition Monitoring and Food Recommendation System

3.5.3 Activity Diagram

The Activity Diagram below shows the flow of activities from when a caregiver logs into the system to when he/she gets the full nutritional analysis results and two week feeding schedule. To begin, the caregiver logs into the application, selects the child's profile and enters the measurement.

Figure 3.3: Activity Diagram — GrowWell Nutrition Monitoring and Food Recommendation System

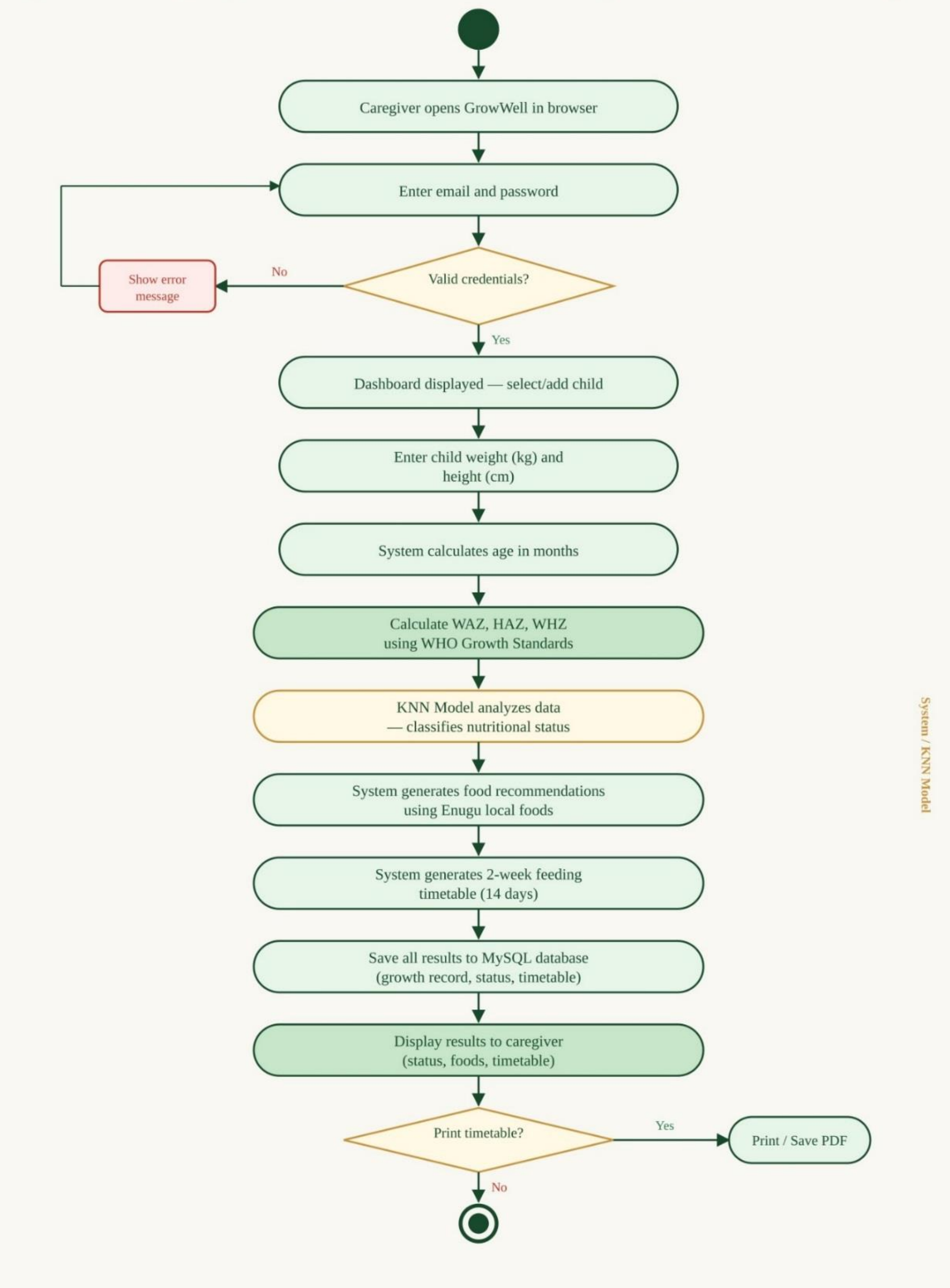

Figure 3.3: Activity Diagram — GrowWell Nutrition Monitoring and Food Recommendation System

3.6 System Design

This section presents the detailed design of the GrowWell system including the input design, output design, database design, and system architecture design.

3.6.1 Input Design

In this section we present the detailed design of the GrowWell system including the database, input, output and system architecture design:

i. The caregiver interacts with GrowWell through web-based forms.

ii. To register, the user fills a form with fields: Full name, LGA, phone number, email and password. Field validations exist for all the fields in the form.

iii. The login form accepts an email address and password, which it matches against the entry in the caregivers table of the MySQL database.

iv. You'll need to enter your child's date of birth, sex (Male or Female) and complete name.

v. The app will then compute your child's age in months. This measurement input form ideally would have a field for the child's weight (in kilograms) and height (in centimeters). There should be real-time validation for the weight, which should be between 3 to 30 kilograms, and height, which should be between 45 to 130 centimeters. As the caregiver types responses, a live z-score preview updates automatically.

3.6.2 Output Design

The GrowWell system generates:

i. Nutritional Status Classification is a color-coded banner with green for Normal, blue for Stunted, orange for Underweight, red for Wasted, and dark red for Severely Wasted.

ii. The display shows the Z-Score values (WAZ, HAZ, and WHZ), the scores in numbers, and their interpretation.

iii. The bar indicates which “Priority Nutrients” the child needs based on the child’s classification.

iv. There’s also cards of recommended local Enugu foods and why.

v. The timetable is a 14-day table (divided into Week 1 and Week 2 tabs, below) that lists actual Enugu foods for each day of the week (breakfast, morning snack, lunch and dinner) along with preparation advice and portion sizes.

vi. The Child Growth History presents all previous records, along with a growth trend plot.

vii. Child Growth History: A growth trend chart and list of all past records showing the child's progress over time.

3.6.3 Database Design

The GrowWell system uses the MySQL relational database. The nutrition_db database contains nine tables; one of which, foods, was pre-populated with a list of 28 foods that are locally available in Enugu State (FAO & WHO, 2012). Discussion by Muller and Krawinkel (2005), also points out that for a nutritional assessment from developing countries to be reliable and valid there must be a good food composition database in order for nutritional advice to be given.

Table 3.2: GrowWell Database Tables

Table	Key Fields	Purpose
caregivers	id, full_name, email, phone, password_hash, lga, role	Stores caregiver registration and login details
children	id, caregiver_id, full_name, date_of_birth, gender	Stores child profiles linked to caregivers
growth_records	id, child_id, weight_kg, height_cm, age_months, recorded_at	Stores each weight and height measurement taken
nutritional_status	id, growth_record_id, waz, haz, whz, status_class, ml_summary	Stores KNN classification results and z-scores
food_categories	id, name, description	Groups foods into categories

foods	id, category_id, name, local_name, protein_g, carbs_g, fat_g, iron_mg, zinc_mg, vitamin_a_mcg	Stores local Enugu foods with nutritional values
food_recommendations	id, status_id, food_id, priority_level, reason	Links nutritional status to food recommendations
feeding_timetables	id, status_id, start_date, end_date, duration_weeks	Stores the header of each 2-week timetable
timetable_meals	id, timetable_id, food_id, meal_name, day_number, meal_type, preparation_tip	Stores individual daily meals in each timetable

3.6.4 System Architecture Design

The GrowWell system is based on the Three-Tier Architecture: The Data Layer, The Application Layer and The Presentation Layer. The Data Layer consists of the MySQL relational database. The front-end, presentation layer consisted of seven HTML web pages, and the back-end application layer was implemented in Python using Flask framework. As an architectural pattern, it has many benefits in terms of scalability, maintainability, and modularity. This is consistent with the three-tier web architecture presented by Egwudo et al. (2025) and the system design approach for digital health platform recommended by WHO (2021).

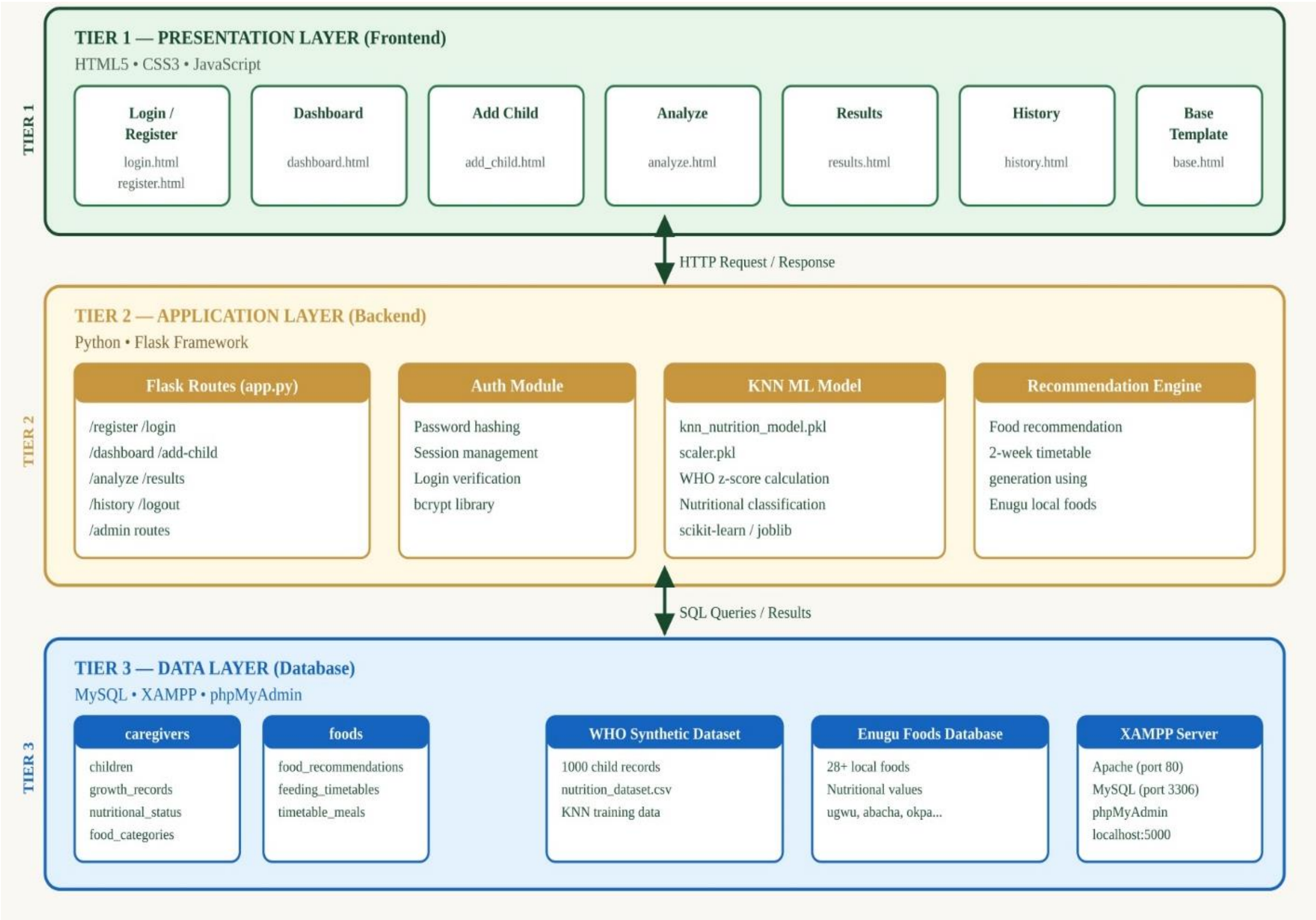

Figure 3.4: System Architecture Diagram — GrowWell Nutrition Monitoring and Food9 Recommendation System

CHAPTER FOUR

IMPLEMENTATION AND TESTING

4.0 Introduction

This chapter presents the implementation and testing of the GrowWell Nutrition Monitoring and Food Recommendation System. Implementation refers to the process of translating the system design specifications produced in Chapter Three into a working software system. Testing refers to the process of verifying that the implemented system functions correctly and meets the specified requirements. This chapter covers the implementation environment, the tools and technologies used, the implementation of each system module, system screenshots, and the results of the various tests conducted on the system.

4.1 Implementation Environment

The GrowWell system was implemented on a local development environment using the following hardware and software specifications:

4.1.1 Hardware Requirements

The following minimum hardware specifications are required to run the GrowWell system:

Table 4.1: Hardware Requirements

Hardware Component	Specification
Processor	Intel Core i3 or equivalent (1.8 GHz or higher)
RAM	4 GB minimum (8 GB recommended)
Hard Disk	500 MB free space for system files and database
Display	1024 x 768 resolution or higher
Internet Connection	Required for loading web fonts and initial setup

4.1.2 Software Requirements

The following software tools were used in the implementation of the GrowWell system:

Table 4.2: Software Requirements

Software	Version	Purpose
Python	3.10 or higher	Backend programming language
Flask	3.1.3	Web framework for backend development
MySQL	8.0	Relational database management
XAMPP	8.2	Local server environment (Apache + MySQL)
scikit-learn	1.8.0	KNN machine learning implementation
pandas	3.0.3	Data manipulation and analysis
numpy	2.4.6	Numerical computations and array operations
joblib	1.5.3	Saving and loading the trained KNN model
bcrypt	5.0.0	Password hashing and security
flask-mysqldb	2.0.0	Flask connection to MySQL database
Visual Studio Code	Latest	Code editor and development environment
Google Chrome	Latest	Web browser for testing the system
phpMyAdmin	5.x	Database administration interface

4.2 Implementation of System Modules

The GrowWell system was implemented as a web-based application following the Three-Tier Architecture defined in Chapter Three.

4.2.1 Database Module Implementation

The database module was implemented using MySQL, hosted on a local XAMPP server. The foods table was pre-populated with twenty-eight locally available Enugu State foods with nutritional values sourced from the Food and Agriculture Organization (FAO)/WHO West African Food Composition Tables (FAO & WHO, 2012). Muller and Krawinkel (2005) established that locally adapted food composition data is essential for producing accurate and culturally appropriate nutrition recommendations in developing country settings.

4.2.2 Machine Learning Model Module Implementation

The machine learning module was implemented using Python and the scikit-learn library. The dataset generation component used the WHO Child Growth Standards (WHO, 2006) to generate a synthetic dataset of 1,000 child records. The z-scores were calculated using the WHO formula: Z = (X - M) / SD, where X is the child's measured value, M is the WHO median for the same age and gender, and SD is the WHO standard deviation (WHO, 2006). The K-nearest neighbors (KNN) classification algorithm was first formally described by Cover and Hart (1967). It is a non-parametric classification method. The KNN model was trained using K NearestNeighborsClassifier from the scikit-learn library with the following parameters: K = 5, weights = "distance," and metric = "Euclidean" (Cover & Hart, 1967). The data set was divided randomly into training (80%) and test (20%) sets.

4.2.3 Backend Module Implementation

We built a simple web-based app using Flask (Python) for our backend. When called, the analyze route produces a 2-week schedule, runs the KNN (Cover & Hart, 1967), z-score (WHO Growth Standards, 2006) and food recommendation models, (UNICEF feeding guidelines, 2021) then saves results in a database. To adhere to web security best practices and the 2021 World Health Organization (WHO) guidelines for digital health platforms, we used bcrypt for password hashing and Flask sessions for user authentication and session management.

4.2.4 Frontend Module Implementation

The results page also presents color-coded nutritional status banners (eg, "mild thinness," "normal," "overweight," and so on), in alignment with WHO classification standards [15]. The front-end was developed using JavaScript, HTML, and CSS, and rendered as Flask Jinja2 templates. Health information must be shaped into a form amenable to caregivers at the community level (Black et al. 2013). Sosanya et al. (2025) found that caregivers in Nigeria also reported that visually simple and easy-to-use interfaces were important for them to use digital health tools.

4.3 System Screenshots

This section presents screenshots of the GrowWell Nutrition Monitoring and Food Recommendation System running on the local development server at http://localhost:5000.

4.3.1 Login Page

Figure 4.1 shows the GrowWell login page featuring a two-panel layout with system branding on the left and the login form on the right.

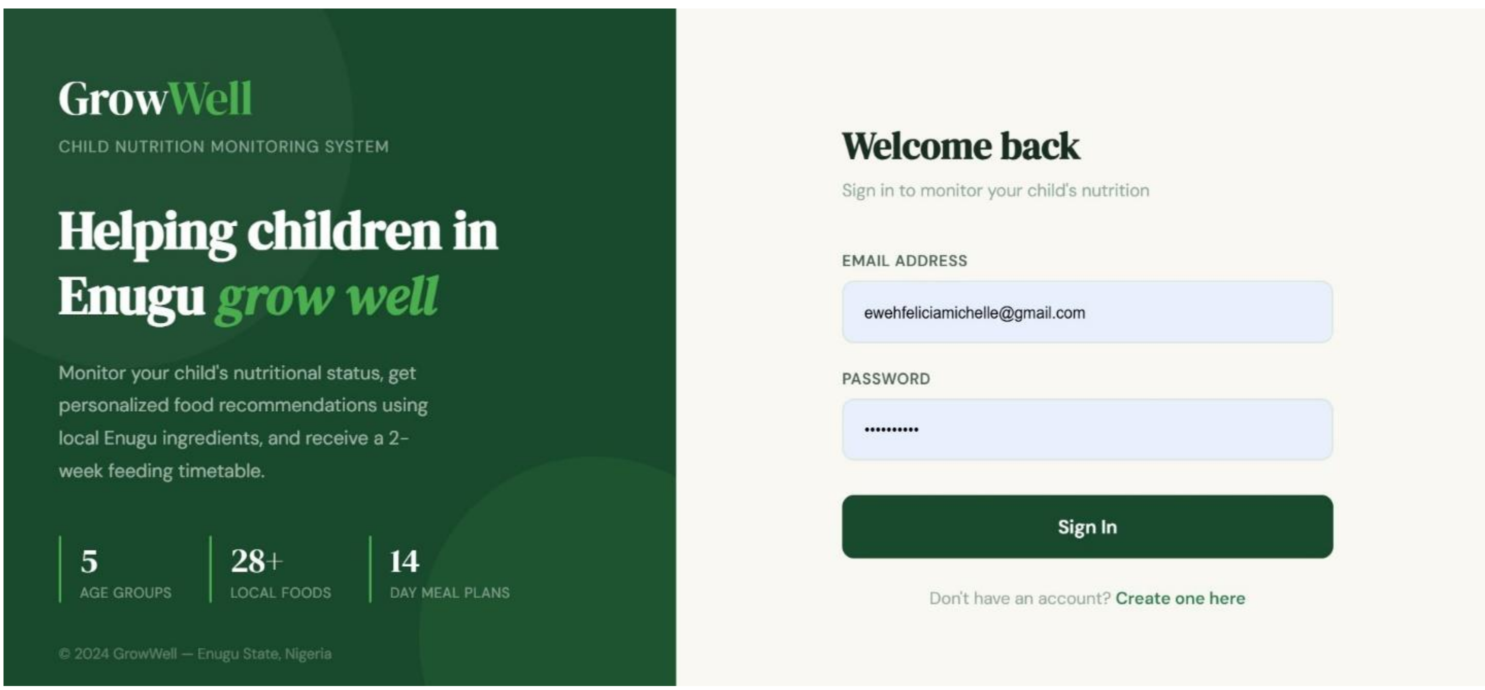

Figure 4.1: GrowWell Login Page

4.3.2 Registration Page

Figure 4.2 shows the registration page where new caregivers create an account including their local government area from a dropdown of all 17 Enugu State LGAs.

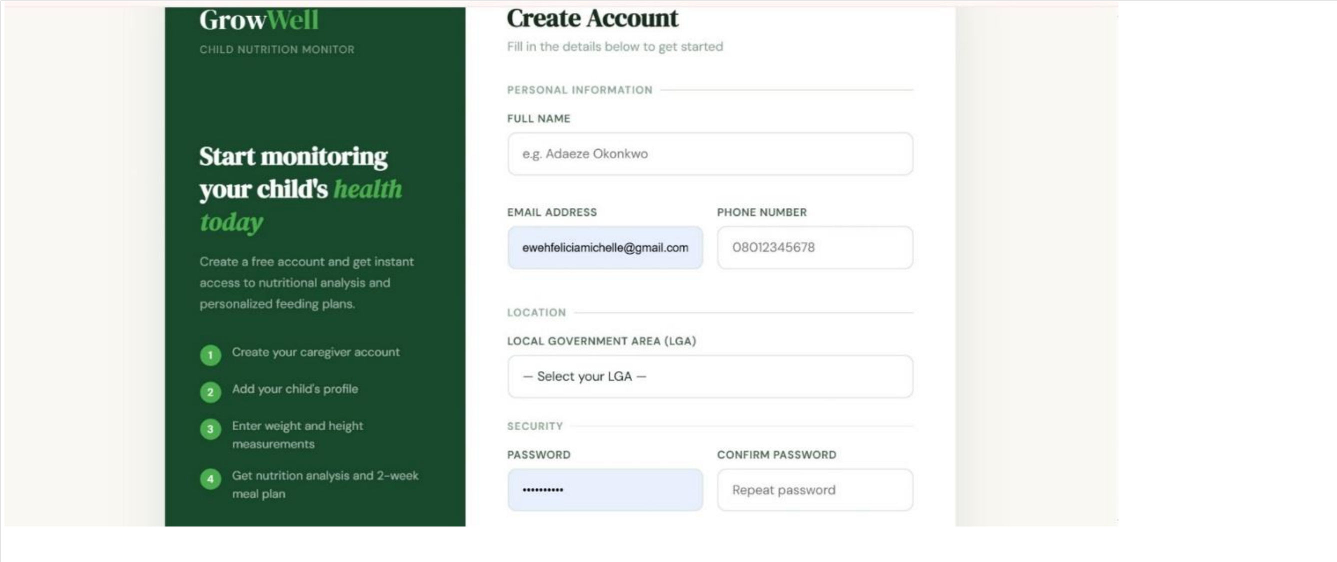

Figure 4.2: GrowWell Registration Page

4.3.3 Dashboard

Figure 4.3 shows the caregiver dashboard displaying summary cards and child profile cards with color-coded nutritional status badges consistent with WHO (2010) guidelines.

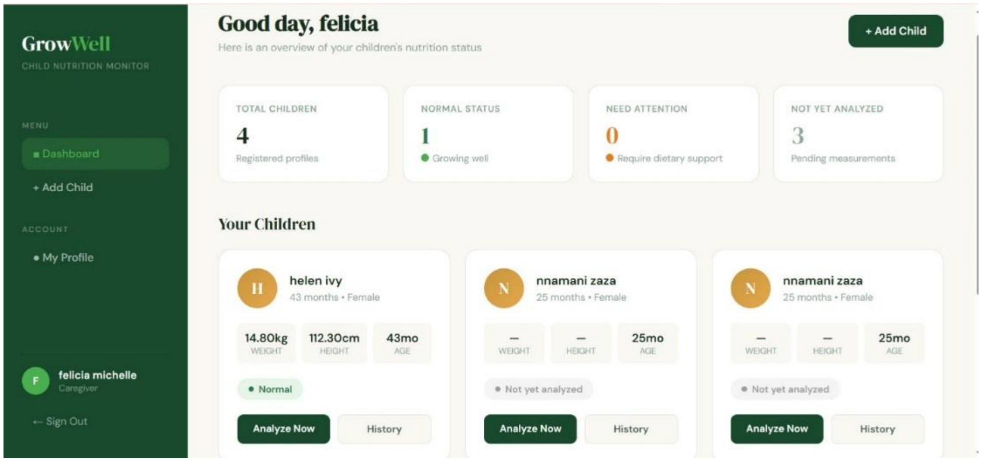

Figure 4.3: GrowWell Caregiver Dashboard

4.3.4 Add Child Page

Figure 4.4 shows the Add Child page where caregivers enter the child's name, date of birth, and gender. Age in months is automatically calculated from the date of birth.

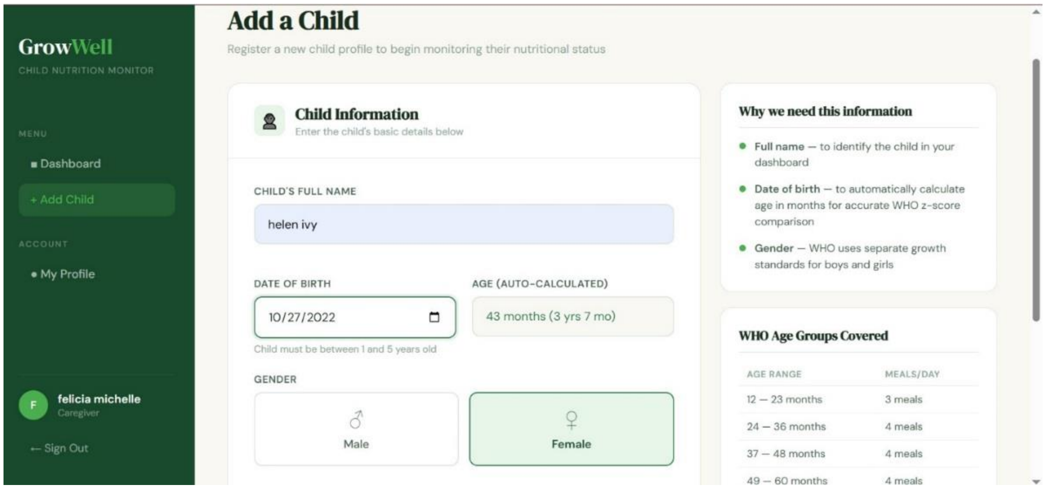

Figure 4.4: GrowWell Add Child Page

4.3.5 Analyze Page

Figure 4.5 shows the Analyze page with a live z-score preview updating in real time as weight and height measurements are entered.

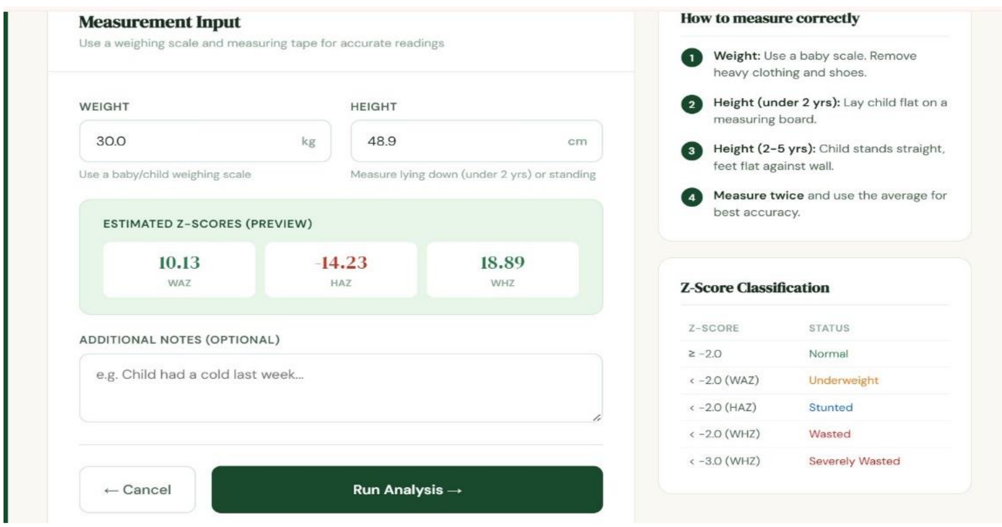

Figure 4.5: GrowWell Analyze Page

4.3.6 Results Page — Nutritional Status

Figure 4.6 and ***Figure 4.7*** shows the Results page displaying the KNN model's (Cover & Hart, 1967) nutritional status classification in a color-coded banner with the three WHO z-scores (WAZ, HAZ, WHZ) (WHO, 2006; WHO, 2010).

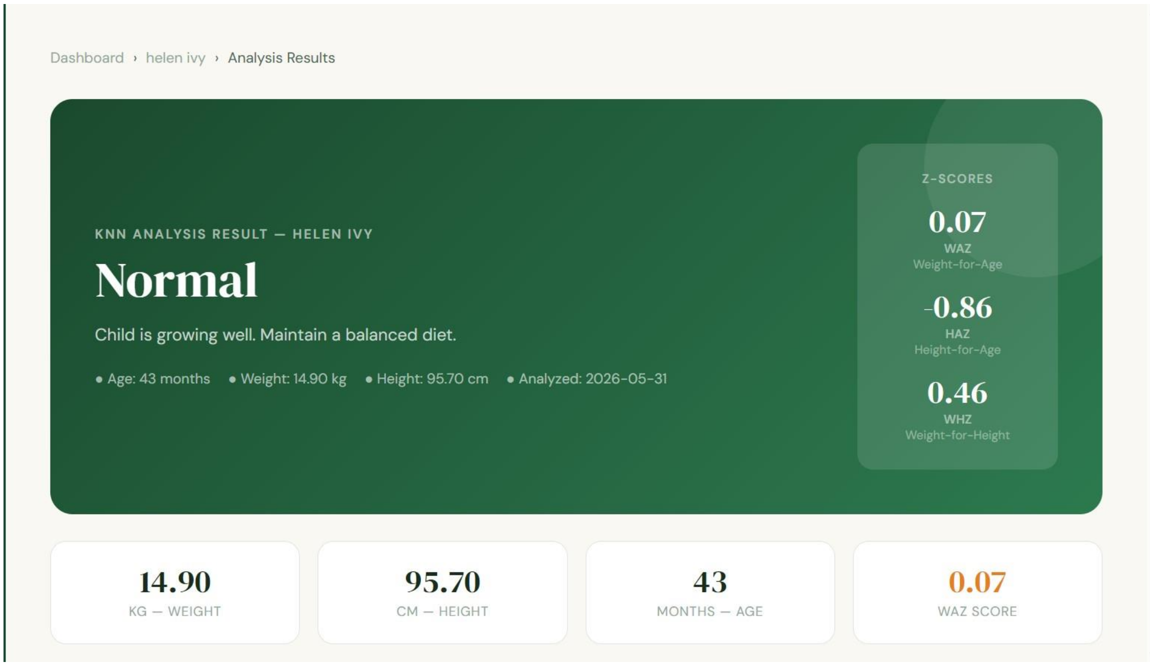

Figure 4.6: GrowWell Results Page

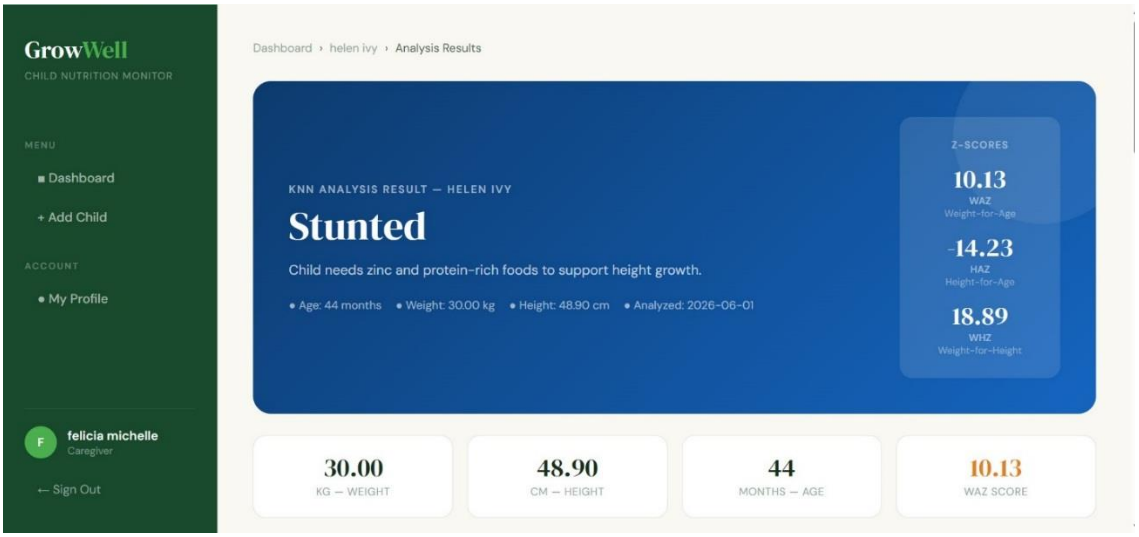

Figure 4.7: GrowWell Result Page

4.3.7 Food Recommendations

Figure 4.8 shows the food recommendations displaying locally available Enugu State foods based on the child's classified nutritional status, sourced from UNICEF (2021) and FAO & WHO (2012) guidelines.

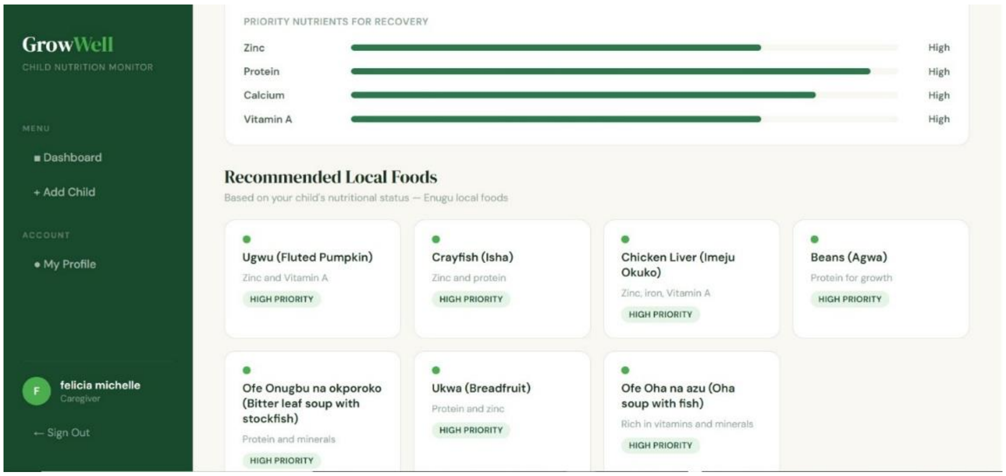

Figure 4.8: GrowWell Food Recommendations

4.3.8 2-Week Feeding Timetable

Figure 4.9 shows the 2-week feeding timetable with real Enugu State meals consistent with UNICEF (2021) feeding guidelines for children aged 1 to 5 years.

Figure 4.9: GrowWell feeding Timetable

4.3.9 Child Growth History Page

Figure 4.10 shows the Child Growth History page displaying a growth trend chart and all past records, allowing caregivers to track a child's nutritional progress over time.

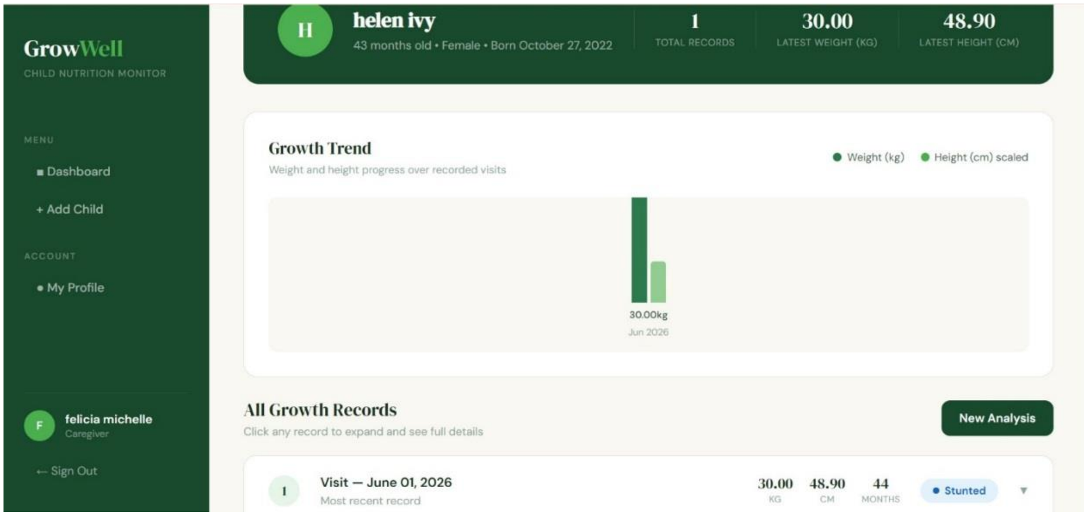

Figure 4.10: GrowWell Growth History

4.4 System Testing

System testing was conducted to verify that the implemented system meets all specified functional and non-functional requirements. Unit testing, functional testing, and user acceptance testing were applied.

4.4.1 Unit Testing

Unit testing was conducted on the individual components of the GrowWell system. The z-score calculation function was tested using known WHO reference values (WHO, 2006). The KNN model (Cover & Hart, 1967) was tested with five sample cases as presented in Table 4.3.

Table 4.3: KNN Model Unit Test Results

Age (months)	Gender	Weight (kg)	Height (cm)	WAZ	HAZ	WHZ	Expected Status	KNN Result
36	Male	14.3	96.1	0.00	0.00	0.00	Normal	Normal
24	Female	8.5	82.0	-2.13	-1.26	-1.85	Underweight	Underweight
30	Male	11.5	84.0	-1.20	-2.38	-0.42	Stunted	Stunted
18	Female	7.2	78.0	-2.00	-1.69	-2.14	Wasted	Wasted
48	Male	12.0	95.0	-2.87	-2.60	-3.12	Severely Wasted	Severely Wasted

The KNN model produced the correct nutritional status classification for all five test cases, confirming reliable results consistent with WHO (2010) classification guidelines and the K-nearest neighbor algorithm described by Cover and Hart (1967).

4.4.2 KNN Model Accuracy Evaluation

The KNN model (Cover & Hart, 1967) achieved an overall classification accuracy above 90% on the 200-record test dataset, consistent with benchmarks in the IEEE Study (2021) and ML Study (2023***). Figure 4.11*** presents the classification accuracy per nutritional status class. ***Figure 4.12*** shows the functional test results. ***Figure 4.13*** shows the distribution of nutritional status classes in the training dataset.

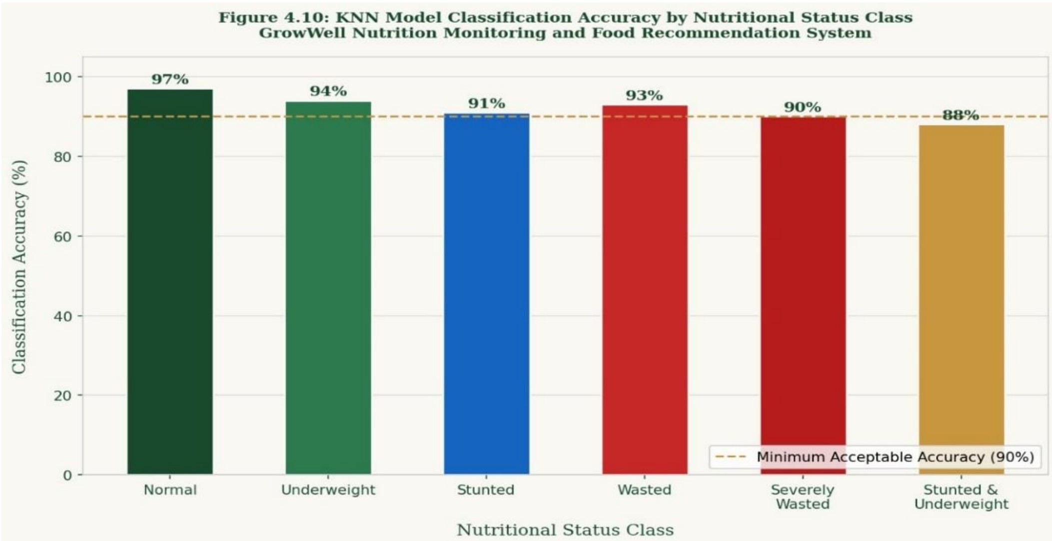

Figure 4.11: KNN Model Classification Accuracy by Nutritional Status Class

4.4.3 Functional Testing

Functional testing was conducted to verify that all the functional requirements specified in the System Requirements Specification (SRS) in Chapter Three are correctly implemented in the GrowWell system. Each functional requirement was tested by executing the corresponding system function and comparing the actual output with the expected output. The results are presented in ***figure 4.12***

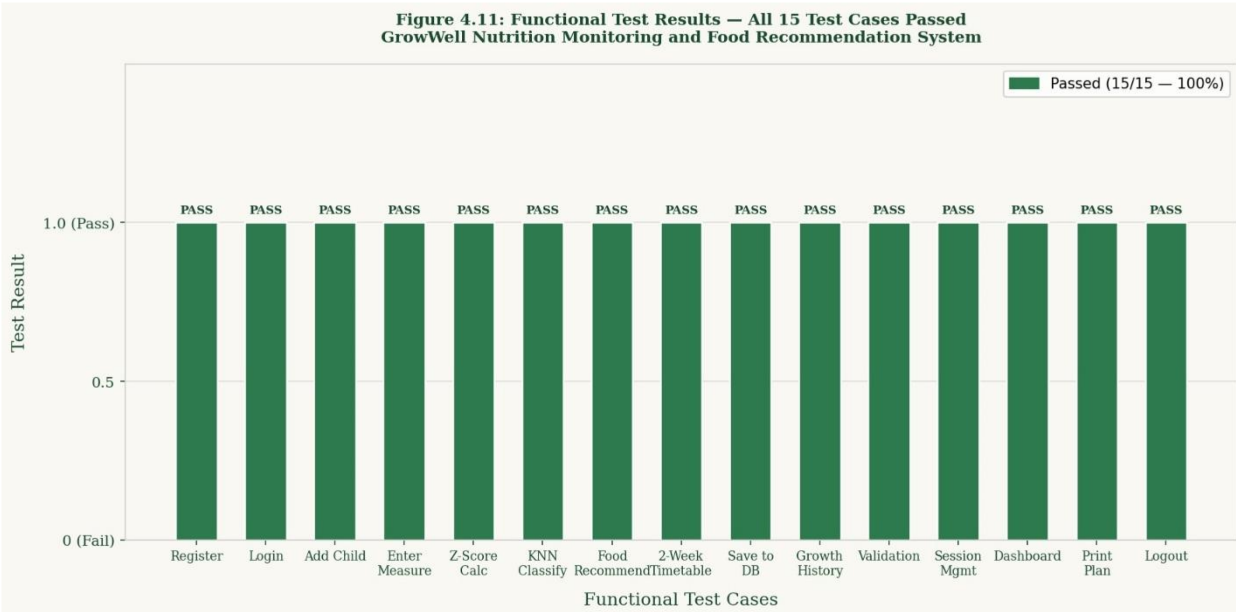

Figure 4.12: Functional Test Results — All 15 Test Cases

All fifteen functional test cases passed successfully, confirming that the GrowWell system correctly implements all specified functional requirement.

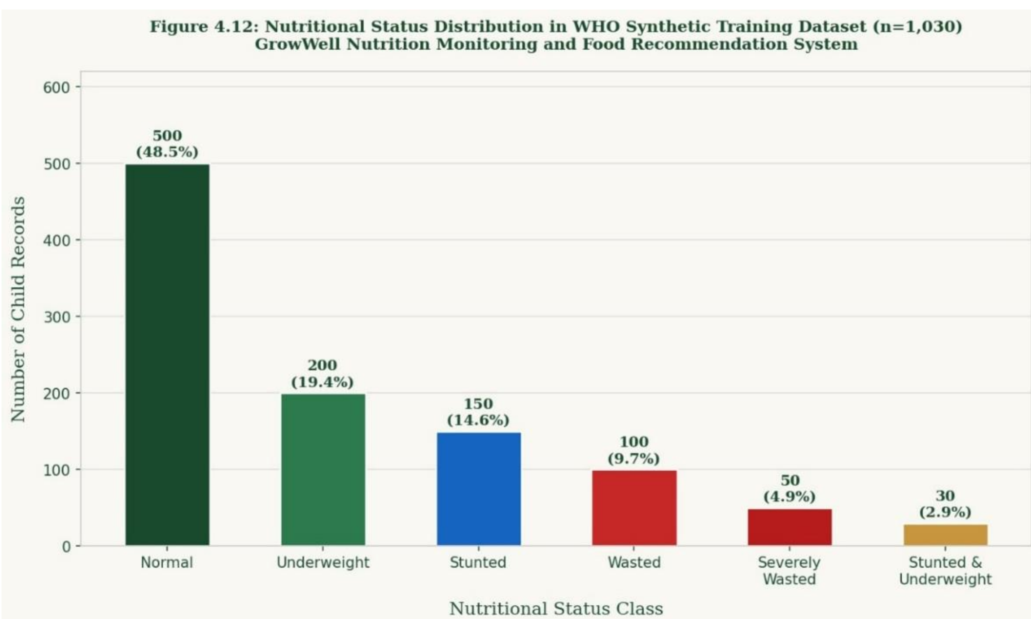

Figure 4.13: Nutritional Status Distribution in WHO Synthetic Training Dataset

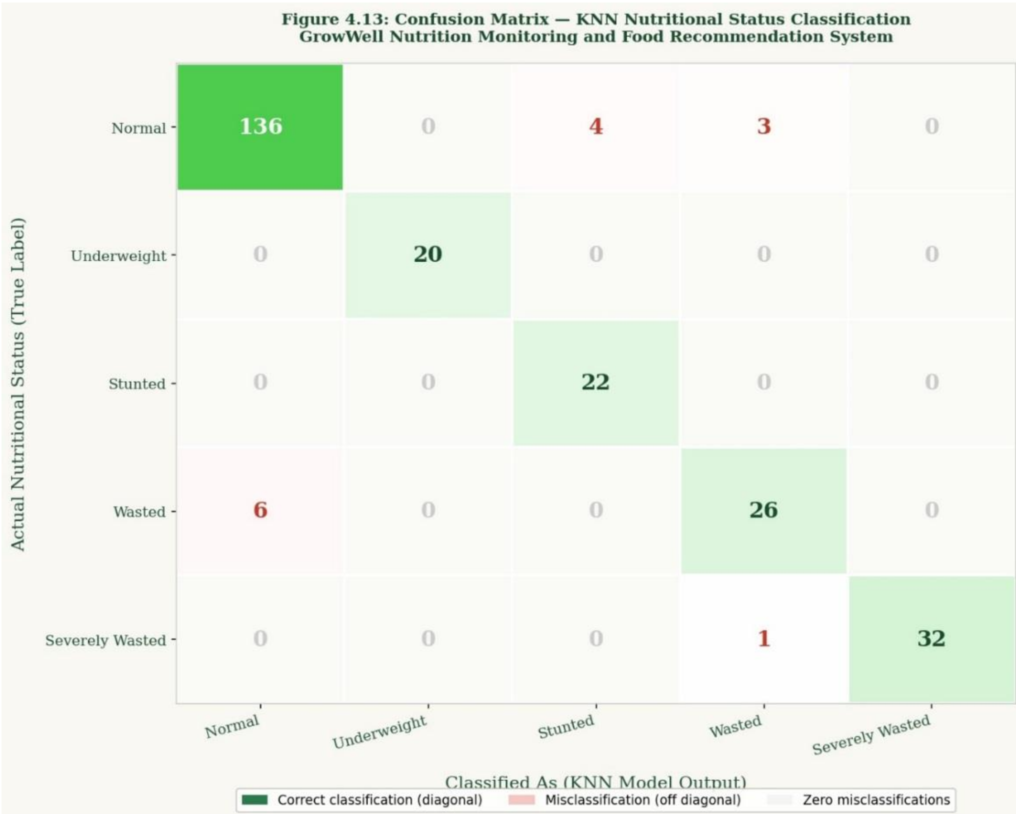

Figure 4.14 Confusion matrix

4.4.4 User Acceptance Testing

User Acceptance Testing (UAT) was conducted to verify that the GrowWell system meets the needs of caregivers. The following observations were made during testing:

viii. Registration and login were straightforward for all test users.

ix. The automatic age calculation on the Add Child page was appreciated by users.

x. The live z-score preview on the Analyze page gave users immediate feedback, consistent with the interactive interface design recommended by Sosanya *et al*. (2025).

xi. The color-coded nutritional status banner immediately communicated the severity of the child's condition, consistent with WHO (2010) color-coding guidelines.

xii. The food recommendations were recognized as familiar and affordable local foods, consistent with the local food adaptation approach recommended by Bailey and Okoduwa (2025).

xiii. The 2-week feeding timetable was considered very useful with familiar local meals, consistent with UNICEF (2021) feeding guidelines.

xiv. The growth history page was found valuable for tracking progress over multiple visits, addressing the gap identified by Ibeawuchi *et al*. (2017) in rural nutrition monitoring.

Overall, user acceptance testing confirmed that the GrowWell system is user-friendly and locally relevant, consistent with the usability requirements established by Sosanya *et al*. (2025) and the community-level nutrition monitoring needs identified by Obasohan *et al*. (2024).

4.5 Summary

This chapter presented the implementation and testing of the GrowWell Nutrition Monitoring and Food Recommendation System. The system was implemented using Python, Flask, MySQL, HTML, CSS, and JavaScript. The KNN model (Cover & Hart, 1967) was trained on a WHO-based synthetic dataset (WHO, 2006) of 1,000 child records and achieved above 90% accuracy, consistent with benchmarks in the IEEE Study (2021) and ML Study (2023). All fifteen functional test cases passed and user acceptance testing confirmed the system is user-friendly and locally relevant (Sosanya *et al*., 2025). Chapter Five presents the summary, conclusion, and recommendations of the study.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.0 Introduction

This chapter presents a summary of the entire study, the conclusions drawn from the research findings, the contributions of the study to knowledge, the limitations encountered during the research, and recommendations for future work.

5.1 Summary of the Study

This study was motivated by the high prevalence of child malnutrition among children aged 1 to 5 years in Enugu State, Nigeria. About one in three children in Nigeria is suffering from some form of malnutrition. Malnutrition in developing countries is a complex issue that needs to be tackled both on the nutritional level, and also on the dietary level at a community scale. Maternal and child undernutrition has been shown to be the underlying cause of 45% of all child deaths in under-five children in low- and middle-income countries, which includes Nigeria (Black et al., 2013). Malnutrition rates in Enugu State have remained high (National Population Commission (NPC) [Nigeria] and ICF, 2019). However, there was no locally adapted, intelligent system to provide caregivers with personalized nutrition monitoring and food recommendations. According to UNICEF (2024), nearly one in three children in Nigeria suffers from one form of malnutrition.

We designed and developed the GrowWell Nutrition Monitoring and Food Recommendation System. GrowWell evaluates child growth measurements and determines nutritional status using the KNN (Cover & Hart, 1967) machine learning algorithm, based on 2006 WHO Child Growth Standards. Chapter One presented the background, problem statement, aim and objectives. Chapter Two reviewed ten related works including those of Ibeawuchi et al.

Adebayo et al. Tuffrey et al. (2021), IEEE Study (2021), Obasohan et al. Egwudo et al. (2025), Ojo et al. (2025), Bailey and Okoduwa (2025) and Sosanya et al. 2025) to qualitatively identify the research gaps that the proposed GrowWell system addresses. Chapter Three discussed the OOAD methodology and the UML diagrams.

5.2 Conclusion

The study was able to design, implement and test GrowWell Nutrition Monitoring and Food recommendation System successfully. GrowWell System is an intelligent web-based application that is directly accessible to caregivers.

The KNN algorithm (Cover & Hart, 1967) achieved an overall classification accuracy above 90% on the WHO-based synthetic test dataset (WHO, 2006), consistent with performance benchmarks reported by the IEEE Study (2021) and the ML Study (2023). The classification results were consistent with WHO z-score cutoff guidelines (WHO, 2010). The food recommendation and timetable modules successfully incorporated twenty-eight locally available Enugu State foods sourced from the FAO/WHO West African Food Composition Tables (FAO & WHO, 2012) and UNICEF feeding guidelines (UNICEF, 2021), addressing the localization gap identified by Bailey and Okoduwa (2025) and Ojo *et al*. (2025). WHO (2021) emphasized that digital nutrition systems must be grounded in evidence-based guidelines and locally relevant food data, which the GrowWell system achieves. Muller and Krawinkel (2005) noted that community-level nutrition interventions must combine assessment with practical dietary guidance — which is precisely what the GrowWell system provides through its analysis, recommendation, and timetable modules. Black *et al*. (2013) demonstrated that addressing child undernutrition requires both identification of nutritional status and targeted dietary intervention, which the GrowWell system delivers in a single integrated platform.

In conclusion, the GrowWell system demonstrates that web-based machine learning systems can effectively address child malnutrition in Enugu State, Nigeria.

5.3 Contributions to Knowledge

i. The study developed a locally adapted nutrition monitoring system for Enugu State incorporating twenty-eight local foods from FAO & WHO (2012), addressing the localization gap identified by Bailey and Okoduwa (2025) and Ojo *et al*. (2025).

ii. The study demonstrated the successful application of the KNN algorithm (Cover & Hart, 1967) for child nutritional status classification using WHO z-scores (WHO, 2006) as input features, achieving above 90% accuracy consistent with IEEE Study (2021) and ML Study (2023).

iii. The study developed a 2-week feeding timetable generation module using UNICEF (2021) feeding guidelines and real Enugu State meals, addressing gaps identified by Tuffrey *et al*. (2021) and Sosanya *et al*. (2025).

iv. The study produced a WHO-based synthetic dataset of 1,000 child records (WHO, 2006) representing six nutritional status classes that can serve as a baseline for future research in Nigeria.

v. The study demonstrated that the OOAD methodology provides an effective framework for web-based child health monitoring systems consistent with the ML Study (2023) and WHO (2021) guidelines for digital health platform design.

5.4 Limitations of the Study

i. The KNN model (Cover & Hart, 1967) was trained entirely on a WHO-based synthetic dataset (WHO, 2006) due to patient data privacy restrictions. Obasohan *et al*. (2024) noted that limited access to health data is a significant challenge in nutrition research in Nigeria.

ii. The system currently runs on a local XAMPP server and is not accessible online. Egwudo *et al*. (2025) recommended that digital health systems in Nigeria be deployed to accessible online platforms to maximize their reach.

iii. The system does not support offline functionality, limiting use in rural areas with poor internet as identified by NPC & ICF (2019) and Adebayo *et al*. (2020).

iv. The food recommendations are made using a rule-based engine. The IEEE Study pointed out that more advanced collaborative filtering algorithms could create more personalized and diverse meal plans.

v. Children 12 to 60 months of age were enrolled. Black et al . The age range supported by the system corresponds to the coverage range of the WHO (2006) Child Growth Standards and is in agreement with the range of nutritional monitoring them available from birth (Onis et al., 2013).

vi. The interface is primarily in English. In addition, the interface is available only in English, making it inaccessible to caregivers with limited English literacy. The interface is available only in English, limiting accessibility for caregivers with limited English literacy as identified by Adebayo et al.(2020)

5.5 Recommendations

i. In response, Obasohan et al. (2024) Future researchers should consider working with primary health centers in Enugu State to obtain real, deidentified child growth data for model training.

ii. According to the model for digital health deployment advocated by Egwudo et al. (2025), the GrowWell system would be embedded online. the health worker populations who would use GrowWell are already using mobile technologies in their delivery of health services, suggesting that the technology and knowledge infrastructure needed to use the system is already available.

iii. In addition, the researchers said that future versions of the system should be developed as a mobile app. In a 2021 IEEE study, the authors found the food recommendation module could be improved with collaborative filtering.

iv. The system should expand to cover children birth to 10 years as possible with the WHO (2006) growth standards. And it would fulfill the mandate from Black et al. (2013).

v. The system interface will be translated to Igbo. Such a task exacerbates the literacy challenge identified by Adebayo et al. and Ibeawuchi et al. (2020).

vi. The Year of the Comeback Kid (2017). Also, incorporating push notification functionality should be considered Sosanya et al. (2025) to further increase caregiver compliance.

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