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A Food recommendation system for weaning of children in Kenya using rule-based technique.

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A Food Recommendation System for Weaning of Children in Kenya using Rule-Based Technique

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Declaration and Approval

Declaration

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the dissertation contains no material previously published or written by another person except where due reference is made in the dissertation itself.

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Approval

The dissertation of Ndemo Dawn Moraa was reviewed and approved for examination by the following:

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Abstract

Childhood malnourishment is a key worldwide health concern that affects millions of children globally. It can lead to stunting, wasting, and underweight conditions, as well as micronutrient deficiencies. These conditions can have far-reaching consequences, including stunted growth and development, suboptimal academic performance, and compromised overall health.

One major cause of childhood malnutrition is poor feeding practices, particularly during the weaning stage. Parents and caregivers often lack the knowledge and resources they need to provide infants and young children with the balanced diets they require. There is also a large human resources gap in the Kenyan healthcare system, where there aren’t enough nutritionists and dietitians to attend to the population and give professional child feeding advice. A way to solve this knowledge gap has been to develop food recommendation systems that help users in making more informed food choices based on their current health status. Many of these systems are tailored for adult populations such as patients with chronic diseases.

This study developed a food recommendation system that is tailored to the specific needs of a child, considering factors such as age, weight and height. The system sought to utilize rule-based technique to develop a food recommendation system that would serve as a decision support system for parents and caregivers. The rule-based system was built using Experta, and contained in a full-stack web application that was developed using Flask and React. A comprehensive and diverse food database was adapted from the Kenya Food Composition Tables. The system provided tailored nutrition feedback on amount and frequency of feeding, as well as nutritionally balanced food recommendations in the suggested meal plan. This system not only considered calorie needs but also emphasized nutrient diversity to ensure that children are getting the key micronutrients they need. The system is also usable by healthcare workers to fill the nutrition technical skills gap in healthcare facilities.

Keywords: *nutrition, weaning, information science, informatics, rule-based technique, decision-support system, recommendation systems.*

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List of Abbreviations

API	Application Programming Interface
CHV	Community Health Volunteer
CHW	Community Health Worker
CPU	Central Processing Unit
FAO	Food and Agriculture Association of the United Nations
IDE	Integrated Development Environment
JME	Joint Malnutrition Estimates
KDHS	Kenya Demographics and Health Survey
KNBS	Kenya National Bureau of Statistics
MOH	Ministry of Health
MUAC	Middle Upper Arm Circumference
PC	Personal Computer
RAM	Random Access Memory
RDA	Recommended Dietary Allowance
REST	Representational State Transfer
SDG	Sustainable Development Goals
SSD	Solid State Drive
TEE	Total Energy Expenditure
UNICEF	United Nations Children's Fund
WHO	World Health Organization

Definition of Terms

Rule-Based Technique	A rule-based technique refers to a method of problem-solving or decision-making where outcomes are determined by a set of predefined rules or conditions, typically expressed in the form of if-then statements, where specific actions or conclusions are triggered based on the satisfaction of certain criteria (Russell et al., 2010).
Recommendation System	A recommendation system is a computational technique used to predict and suggest items or content that are likely to be of interest or relevance to a user (Ricci, 2011).
Weaning	Child weaning refers to the gradual process of transitioning an infant from breastfeeding or formula feeding to consuming solid foods and eventually becoming independent of breast milk or formula as the primary source of nutrition (Bhandari, 2016).

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I would also like to extend my heartfelt appreciation to my classmates for their collaboration and shared experiences. Their support has been a source of inspiration and motivation.

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Dedication

This thesis is dedicated to my father, Mr. Bernard M. Ndemo, for his immense support towards the pursuit of this Master's Degree, as well as for his encouragement and nurture towards me as his daughter. I acknowledge and appreciate your tremendous care and provision, and I am grateful that you have never lost faith in me.

Chapter 1: Introduction

1.1 Background of the Study

Malnutrition is a critical public health burden that affects millions of children below the age of five worldwide. Stunting, wasting, underweight and hidden hunger are all types of undernutrition that can seriously affect a child's physical and cognitive development. Stunting is a state in which a child's height is below the expected level for their age. It is a long-term consequence of inadequate nutrition and chronic infections. Wasting is a state in which a child's weight is below the expected level for their height. It is a short-term consequence of inadequate food intake or acute illness. Underweight is a state in which a child's weight is below the expected level for their age. It can be caused by inadequate nutrition intake, chronic infections, or a blend of both. Lowe (2021) defines hidden hunger as "the presence of multiple micronutrient deficiencies (particularly iron, zinc, iodine and vitamin A), which can occur without a deficit in energy intake as a result of consuming an energy-dense, but nutrient-poor diet" (p. 283).

One of the most important periods for preventing malnutrition is during the weaning transition. Weaning refers to the period when infants are introduced to solid foods. The World Health Organization (WHO) advocates for exclusive breastfeeding for the first 6 months of an infant's life. Breast milk is nutritionally sufficient and protects against infection by providing antibodies from the mother to the child. However, beyond the first 6 months, breast milk can no longer provide adequate nutrition and new foods must be introduced to complement breastfeeding, also referred to as complementary feeding (WHO, 2021).

When children are ready for complementary feeding, the current practice for parents and caregivers in Kenya is to seek child nutrition advice from healthcare workers in healthcare facilities, or fellow parents and older women in the community. Access to healthcare professionals with sufficient nutritional training to meet the population's needs is significantly limited. As a result, most parents fall back on fellow parents for support and advice, which often leads to the continued perpetuation of misleading and harmful child-feeding practices.

Information and Communication Technology can be employed to fill the gap that currently exists through a food recommendation system. A food recommendation system for weaning can help parents access food suggestions that meet the minimum dietary recommendations based on the child’s age and needs. This can help to ensure that children are receiving the nutrients they need to grow and develop properly.

Additionally, in facilities that lack enough nutrition staff, a food recommendation system can be used by Community Health Workers (CHWs) and Community Health Volunteers (CHVs) to conduct nutrition education and combat childhood malnutrition in their respective regions. CHWs and CHVs can use the system to generate personalized food recommendations for families based on their children’s needs. ICT can also be used to create and disseminate educational materials on child nutrition. These materials can be provided to parents and caregivers through mobile phones, tablets, and other devices. They can also be displayed in healthcare facilities and community centres.

1.2 Problem Statement

Globally, undernutrition accounts for 45% of all child deaths annually (WHO, 2021). The Kenya Demographic and Health Survey (KDHS) reports that 18% of children under the age of five in Kenya are stunted, 5% of children below the age of five are wasted, and 10% of children below the age of five are underweight. Only 31% of children aged 6-23 months were fed a minimum acceptable diet, meaning an adequately diverse diet, with appropriate feeding frequency (KNBS & ICF, 2023).

Soliman et al. (2021) reviewed various published research that concluded that early childhood malnutrition, in particular nutritional stunting, has both direct and longstanding effects on a child’s health, even into adulthood. Some of the effects include difficulty learning and a heightened risk of developing non-infectious diseases such as diabetes and hypertension. UNICEF suggests that a contributing factor to childhood malnutrition is a lack of information on the parents' or caregivers' part, on what to feed children at each stage of their growth and development (UNICEF, 2018).

With nutrition being a fairly new field in Kenya, there exists a substantial technical skills gap in terms of trained nutritionists and dietitians. In 2018, there was an estimated 5,000 registered nutritionists and dietitians in Kenya, with a population of over 53 million people, thus giving a ratio of one nutritionist or dietitian for every 10, 600 people (Ministry of Health, 2018).

One way to bridge the gap in access to information on nutrition is by developing food recommendation systems that can be used by the target population to access food recommended by health and nutrition guidelines. Existing food recommendation systems are not tailored to the specific nutritional needs of weaning children. For example, Shari et al.'s Rule-Based Technique (2019) focuses primarily on predefined allergies, and Thongsri et al.'s Collaborative Filtering and Knapsack Method (2022) neglects the health status of users and restricts calorie calculations to adults. DIETOS by Agapito et al. (2018), which employs content filtering, falls short in its ability to recommend specific foods crucial to a balanced diet. Namgung et al. (2019) took an Internet of Things (IoT) approach by using a Smart Plate to ensure that young children were eating well balanced meals while at school. The approach, however, has limited scalability and applicability due to the complexity of the IoT approach.

These findings highlight the need for a food recommendation system that is customized for weaning children, while also being easy to utilise and access. Such a system would take into account the child's individual nutritional needs and provide recommendations for age-appropriate meals. The development of such a system would require collaboration between experts in child nutrition, and technology. This system bears a possibility to meaningfully better child nutrition outcomes during the weaning stage.

1.3 Objectives of the Study

1.3.1 General Objective

The chief objective of this study is to develop a food recommendation system for weaning that will help parents, caregivers and healthcare workers to develop a diverse and adequate meal plan for children in the weaning stage.

1.3.2 Specific Objectives

i. To define the key nutritional requirements for children in the weaning stage
ii. To analyse the weaknesses of existing current food recommendation systems
iii. To develop a food recommendation system for weaning
iv. To test the effectiveness of the developed food recommendation system for weaning

1.4 Research Questions

i. What are the specific nutrient requirements for children in the weaning stage, based on their age, weight, and growth rate?
ii. What gaps exist in current approaches used in recommending foods for child weaning?
iii. What are the usability and user interface design considerations for ensuring that the system is user-friendly for parents and caregivers?
iv. Are the food recommendations made by the system nutritionally appropriate for children in the weaning stage?

1.5 Justification of the Study

The system assists parents and caregivers in determining appropriate foods to give their children based on age, developmental stage, and the associated nutritional needs of each stage. The system takes into account various nutrients of public health concern such as protein, energy, fat, Vitamin A, iron, and zinc among others, and recommend foods to meet these requirements. The system can also be used by Community Health Workers, Community Health Volunteers, Nurses and Nurse Aides, Clinical Officers, and other healthcare workers who work in settings that may not have enough nutrition staff. This therefore helps parents and caregivers as well as other healthcare workers in protecting their children from malnutrition and its long-term effects.

1.6 Scope and Limitation of the Study

This study concentrated on developing a food recommendation system for children aged 6 months to 23 months. The study developed and implemented a food recommendation system specifically designed for weaning. This system considered individual child's macronutrient and key micronutrient needs based on their age, weight, height, and other nutritional characteristics. The system was developed to recommend foods that are commonly eaten in Kenya.

Nutritional recommendations for adults, children over two years of age, or children under six months of age are not within the scope of this study, as the calculations and recommendations made are specific to children 6-23 months old. The research did not fully capture all cultural and regional dietary customs and variations. The system does not consider external factors such as the child's economic situation, as food cost and accessibility is not taken into account while tailoring the food recommendations. As prior mentioned, food recommendations are made of foods commonly eaten in Kenya, therefore some of the foods may not be readily available in other geographical locations. The recommendations of the system are therefore not universally applicable to all children below the age of two.

Chapter 2: Literature Review

2.1 Introduction

This chapter centres on the important phase of child weaning. Section 2.2 explores current child weaning guidelines, recommended by the Kenyan Ministry of Health and the WHO, with focus on frequency of feeds. Section 2.3 investigates the various techniques used in determining a child's specific nutrient and energy requirements. Section 2.4 dives into the world of technology and artificial intelligence, particularly machine learning techniques, which have led to the development of smart systems used in food and nutrition recommendations. Section 2.5 reviews relevant research and evaluates four similar works in this area. By combining all this information, a conceptual framework is created that brings together child weaning, malnutrition management, and rule-based food recommendation systems.

2.2 Child Weaning Guidelines

The WHO and UNICEF recommend that newborns receive breastmilk only, for the first six months of life. At this stage, breastmilk provides all the nutrients a child needs, provides enough water, contains antibodies and probiotics that build a child's immunity and is safe to consume, protecting infants from various infections. After six months, breastmilk can no longer meet the growing energy and nutritional needs of the child, and there is a need to introduce other foods to meet these growing needs (WHO, 2021).

Introducing solid foods before six months can assert a significant effect on a child's long-term well-being even into adulthood. Research done by Cottrell and Ozanne showed that poor feeding in early infancy could result in a child being highly predisposed to obesity and its associated metabolic syndrome. This means that children who are underfed or overfed during early infancy could later develop metabolic health complications such as insulin resistance, diabetes, and hypertension among others (Cottrell & Ozanne, 2008). Poor childhood nutrition can lead to a cycle of multigenerational disease, where poorly fed children become adults dealing with metabolic diseases such as diabetes and hypertension, as well as associated maternal and gestational health risks such as gestational diabetes (Gluckman et al., 2009).

Various studies have presented that there is no evidence suggesting that parents should restrict certain foods in the intakes of newborns and young children out of concern for potential allergic effects. Julia, Macia and Dombrowitcz (2015) posed that early exposure to food allergens was possibly advantageous in protecting against allergies and asthma in children (Julia et al., 2015). A study on whether early introduction of eggs can prevent egg allergies concluded that early introduction of possibly allergenic foods is beneficial, and that delayed introduction resulted in a higher risk of developing allergies and sensitivities (Koplin et al., 2010). It is therefore safe to introduce a variety of foods to young children, including cow's milk, peanuts, eggs, and other commonly avoided foods (Romero-Velarde et al., 2016).

In summary, the WHO recommends that weaning be timely, meaning weaning is started when breastfeeding is no longer sufficient to meet energy needs, adequate meaning it meets the nutrient and energy needs, and safe meaning it is prepared and stored in a clean manner to prevent food-borne illnesses (WHO & UNICEF, 2003). Table 2.1 below summarises the child weaning guidelines.

Table 2.1 Summary of Child Weaning Recommendations (Ministry of Health, 2010; World Health Organization, 2009).

Age	Texture	Frequency	Amount
6-8 months	Thick porridge, mashed or pureed foods	2-3 meals a day Frequent breastfeeding	2-3 tablespoons to ½ a 250 ml cup
9-11 months	Finely chopped, diced or mashed foods	3-4 meals a day 1-2 snacks	½ to ¾ of a 250ml cup
12-23 months	Chopped into small pieces or mashed if needed	3-4 meals a day 1-2 snacks	¾ to full 250ml cup

2.3 Child Nutrient and Energy Requirements

As children grow from 6 to 23 months of age, their nutrient and energy requirements undergo significant changes. During this period, infants transition from solely relying on breast milk or formula to incorporating solid foods into their diet. This transition is essential to meet their escalating nutritional demands (Kuo et al., 2011). As they become more active and their bodies develop, their need for crucial nutrients such as protein and micronutrients increase. Furthermore, their energy needs rise to support the expansion of body tissues and increased physical activity. Therefore, it becomes vital for caregivers to ensure a diverse and nutrient-rich diet to meet these growing nutritional requirements, laying a strong foundation for the child's overall growth and development (WHO & UNICEF, 2003).

Children who continue to receive a significant portion of their daily nutrition from breastfeeding or formula may have slightly lower energy requirements from complementary foods compared to those who rely less on breast milk or formula. However, it's essential to note that the energy requirements for complementary feeding are not solely determined by the amount of breast milk or formula intake. Factors such as a child's growth rate, activity level, and individual metabolism also influence these requirements. Therefore, tailoring the food intake to meet the specific energy requirements of each child is vital to ensure they receive adequate nutrition and support their healthy development during this transitional period (Romero-Velarde et al., 2016).

2.3.1 Calculating Energy Requirements

Energy is measured in terms of kilocalories (kcal), often simply referred to as calories. On average, infants and young children require more calories per kilogram of body weight, compared to adults (Faizan & Rouster, 2023). This is due to higher energy needs as they undergo a growth spurt. Adults need 30-40 kcals/kg, whereas infants and young children need an average of 108 kcal/kg (Ministry of Health, 2010).

The Food and Agriculture Organization (FAO) recommends the following parameters, listed in Table 2.2 below, used in calculating energy requirements for infants and young children:

Table 2.2 Summary of Child Energy Requirements. Source: (Food and Agriculture Organization of the United Nations et al., 2004)

Age	RDA Calories	RDA Proteins
0-3 months	100-120kcal/kg	2.2g/kg
3-6 months	110 – 115 kcal/kg	2.2g/kg
6-12 months	90-110 kcal/kg	2.0g/kg
1-3 years	100-105 kcal/kg	1.8g/kg

4-5 years	85-100 kcal/kg	1.5g/kg

2.3.2 Key Micronutrient Requirements

There are key vitamins and minerals which are necessary for developing a child's immunity and general health that must be acquired from the diet. If these vitamins and minerals are deficient in the diet, the child may suffer from ***hidden hunger***, which is a form of malnutrition that may not be visible to the naked eye. A child may otherwise appear to be of healthy weight and height, but the various micronutrient deficiencies can cause long-term health and immunity consequences (Lowe, 2021). There are several critical micronutrients that a child needs in their diet. However, Vitamin A, iron, iodine and zinc are the essential micronutrients that have been observed to be the cause of most cases of micronutrient deficiency in children.

Vitamin A is a key micronutrient that is fat-soluble. It is essential for various body functions, mainly vision, immunity and reproduction. Vitamin A exists in food in two varieties, retinol and beta-carotene. Retinol is found in animal food products such as liver, fish, dairy and eggs. Beta-carotene originates from plant sources such as carrots, sweet potatoes, spinach and kale. A deficiency in Vitamin A results in blindness due to damage to the retina and cornea (Stevens et al., 2015).

Zinc is an essential trace mineral vital for immunity, cell growth and repair, wound healing, skin health, digestion and fertility. Zinc deficiency results in weakened immunity, stunted growth and delayed puberty, skin problems such as eczema, and digestive problems such as diarrhoea. Good sources of zinc include meat, fish, legumes, whole grains, nuts and seeds (Roohani et al., 2013)

Iron is essential for blood production as it is a component of haemoglobin, the protein that binds to and transports oxygen to cells. Cells then use this oxygen for aerobic respiration to metabolise energy needed for life support and muscle function. Iron deficiency leads to iron deficiency anaemia, which is characterized by lethargy and weakness in children. Iron-deficient children are more susceptible to infections. Ron is found in meat, fish, beans and whole grains, among other foods (Briguglio et al., 2020).

Iodine is an necessary mineral needed for the synthesis of thyroid hormones. Thyroid hormones are responsible for regulating growth and metabolism. Iodine is mostly found in seafood and seaweed and is difficult to acquire from diet alone. For this reason, many governments around the globe carry out iodine fortification of salt and various cereals, to prevent iodine deficiency in their population. Iodine deficiency results in goitre, cretinism in children, and hypothyroidism. Hypothyroidism can indirectly lead to obesity and related metabolic diseases such as diabetes. (Sorrenti et al., 2021).

Table 2.3 below, adapted from MOH, lists the recommended nutrient intakes for children for various essential micronutrients (Ministry of Health, 2010).

Table 2.3 Recommended Nutrient Intakes for Children

Nutrient	1-3yrs	4-6yrs	7-9yrs
Energy (kcal)	1300	1800	2400
Protein (g)	16	24	28
Vitamin A (μg RE)	400	500	700
Vitamin D (μg)	5	5	5
Vitamin E (mg α-TE)	6	7	7
Vitamin K (μg)	15	20	25
Vitamin C (mg)	30	30	35
Vitamin B_1 (mg)	0.5	0.6	0.9
Vitamin B_2 (mg)	0.5	0.6	0.9
Niacin (mg NE)	6	8	12
Vitamin B_6 (mg)	0.5	0.6	1.0
Folate (μgaffe/day)	160	200	300
Vitamin (B_{12})	0.9	1.2	1.8
Calcium (mg)	500	600	700
Phosphorus (mg)	800	800	800
Magnesium (mg)	60	70	100
Iron (mg)	10	10	10
Zinc (mg)	10	10	10
Iodine (μg)	75	110	100
Selenium (μg)	17	21	21

2.4 Rule-Based Technique for Recommendation Systems

Rule-based technique is a type of algorithm that uses a set of IF-THEN rules to make decisions. Each rule consists of a condition that must be met and an action that will be taken if the condition is true. Rule-based technique is easy to understand and interpret, and it can be very effective in tasks that involve simple decision-making processes (Masr et al., 2019). The rules to be used in rule-based technique are formulated by domain experts who are knowledgeable and experienced in the relevant field. The knowledge is encoded into rules, which are then refined to represent an expert's decision-making process (Sydenham & Thorn, 2005).

Rule-based techniques, also known as expert systems, emerged as one of the earliest forms of artificial intelligence in the 1960s and 1970s (Luger & Stubblefield, 1993). These systems rely on a knowledge base comprising a set of handcrafted rules that represent domain-specific expertise. By applying these rules to input data, rule-based systems can perform tasks such as diagnosis, classification, or decision-making (Jackson, 1999). Despite their early prominence, rule-based techniques have limitations in their ability to handle complex, real-world problems characterized by uncertainty and large amounts of data. The rise of machine learning, particularly deep learning, has shifted the AI landscape, with such data-driven approaches often outperforming rule-based systems in flexibility and scalability (Russell et al., 2010). However, rule-based techniques still retain value in specific domains where explainability and transparency of the decision-making process are paramount.

A study done in 2013 used the rule-based technique to develop a decision support system for the intensive care unit (Herasevich et al., 2013). In the case of the food recommendation system for weaning of children, nutrition knowledge and recommendations from nutritionists and dietitians were encoded into IF-THEN rules, which were then applied to emulate their decision-making process and consequent recommendations. Abhari et al. (2019) carried out a review of 25 nutrition recommendation systems and found that rule-based techniques were applied in many of them. One such study was done by Rehman et al. (2017) where the authors utilised rule-based technique to determine a user's nutritional needs based on their medical reports.

2.4.1 Components of Rule-Based Technique

Rule-based systems are a foundational approach to artificial intelligence. Their primary components work in conjunction to imitate the reasoning and decision-making processes of human experts. Here's an overview of each component:

2.4.1.1 Knowledge Base

As the core of a rule-based system, the knowledge base acts as a repository of facts, rules, and heuristics relevant to the specific domain the system addresses. These rules are typically expressed in a structured "IF-THEN" format, where the "IF" part (antecedent) specifies a condition, and the "THEN" part (consequent) describes the resulting action or conclusion ,Techniques like production rules, decision trees, semantic networks, or frames are commonly used to represent knowledge (Russell et al., 2010). Techniques like structured interviews with domain experts, analysis of existing data, or machine learning can be used to acquire knowledge.

2.4.1.2 Inference Engine

The inference engine acts as the brain of the rule-based system. It processes information from the knowledge base, matches it against input data, and applies logic to derive conclusions or trigger actions. Common techniques include forward chaining and backward chaining (Giarratano & Riley, 2006).

2.4.1.3 Fact Base

This component stores temporary data, facts asserted by the user, and intermediate results inferred by the system during processing. The contents of this fact base change as the system evaluates rules and draws conclusions.

2.4.1.4 User Interface

The user interface facilitates interaction between the user and the rule-based system. It allows users to input data, queries, and receive explanations or recommendations. The user interface's design is important to ensure ease of use and a clear understanding of the system's reasoning processes.

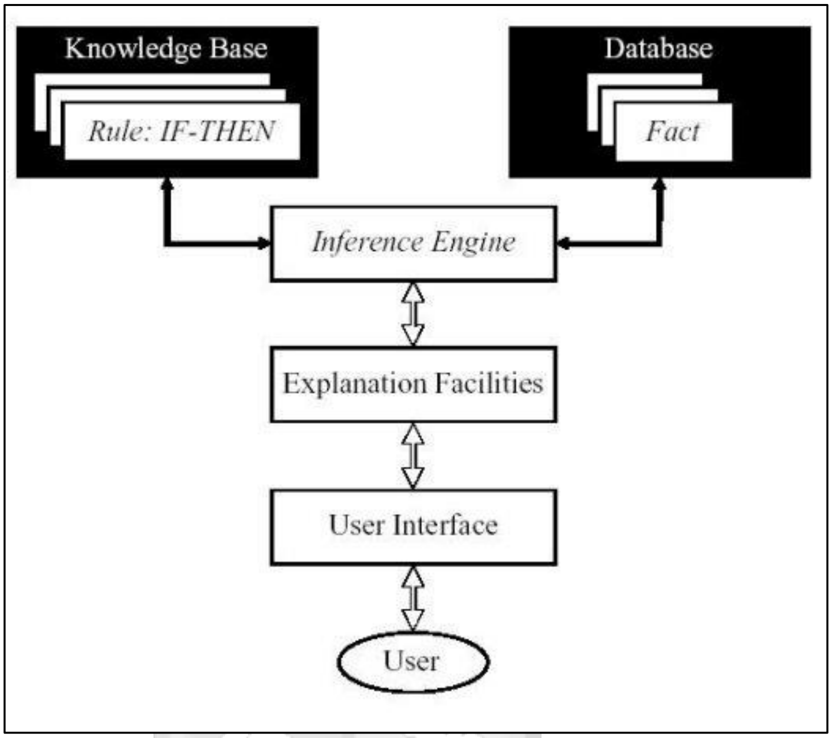

Figure 2:1 Structure of a Rule-Based Expert System (Ogidan et al., 2018)

2.4.2 Inference Mechanisms

As prior mentioned, inference mechanisms are the reasoning strategies employed by rule-based system's inference engine to derive conclusions or trigger actions based on information in the knowledge base and the current fact base. The two classic inference mechanisms are forward chaining and backward chaining.

2.4.2.1 Forward Chaining

Forward chaining, also known as data-driven reasoning, is an inferencing strategy that starts with known facts and applies rules to infer new information (Masr et al., 2019). It progresses from the initial state towards possible goal states. If the antecedent (IF) portion of a rule matches existing data, the rule is fired, and the consequent (THEN) portion adds new information to the working memory. This iterative process continues until no additional rules can be applied, or a predefined goal is reached.

2.4.2.2 Backward Chaining

Backward chaining, or goal-driven reasoning, begins with a hypothesized goal or conclusion and works backward to determine if the facts support it (Neapolitan & Jiang, 2018). The system searches the knowledge base for rules whose consequent (THEN) matches the goal. If a matching rule exists, the antecedent (IF) of that rule becomes a new sub-goal to prove. This method recursively searches backward until either the initial facts validate the goal, or no further rules lead to the goal, indicating failure

2.4.3 Experta Library for Rule-Based Systems

Experta is a Python library designed for building rule-based systems, also known as expert systems. It provides a flexible framework for representing domain knowledge and implementing reasoning mechanisms within Python applications. Experta supports the creation of knowledge bases using production rules, expressed in a clear and readable format close to natural language. It offers both forward chaining and backward chaining inference mechanisms, allowing for data-driven and goal-driven reasoning approaches. Experta allows for the declaration and dynamic modification of facts, facilitating interaction with changing data. The library can provide rudimentary explanations of how it arrived at its conclusions, enhancing transparency in decision-making.

Experta has applications in various areas where codifying expert knowledge is valuable such as in Decision Support Systems. These are useful for guiding users through complex decision-making processes (e.g., medical diagnosis, troubleshooting systems). The food recommendation system for weaning falls under this classification. It has also been applied in automating tasks based on defined rules and conditions such as intelligent alerts. This study applies Experta in the development of the rule-based system, as it allows for the encoding of nutrition rules and provides and inference engine to compare the user provided data with the encoded nutrition expert knowledge.

2.5 Related Works

As malnutrition remains to be a global public health concern, various researchers have developed food recommendation systems to provide access to healthy and nutritionally balanced food recommendations. A variety of techniques have been utilised in both supervised and unsupervised machine learning. Some of the systems are discussed below.

2.5.1 Menu Recommendation System Using Smart Plates for Well-Balanced Diet Habits of Young Children

Namgung et al. (2019) a menu recommendation system using smart plates to prom well-balanced diet habits in young children. The system utilizes smart plates that weigh food before and after each meal to determine the amount of food consumed. This information, along with data on the nutritional content of the food, is used to calculate the child's nutrient intake. The system then generates personalized menu recommendations based on the child's age, gender, and individual nutrient needs. The study used data from 10 children in a day care center and tracked their food intake for one month. The data collected included the weight of food consumed, type of food, and the child’s age, gender, height, and weight.

The system showed promise in predicting the growth rate of the children based on their nutrient intake, as well as identifying potential nutrient deficiencies. However, the study used a small sample size of 10 children, and additionally, the use of smart plates may not be a scalable solution. Lopez-Barreiro et al. (2023) described the study by Namgung et al. (2019) as having a narrow focus that failed to account for the multi-faced nature of health, and therefore fell short in addressing the full picture of well-being for children.

2.5.2 Mobile Application of Food Recommendation for Allergy Baby Using Rule-Based Technique

Shari et al. (2019) developed a mobile application to assist parents and caregivers of babies with allergies in making food recommendations. They sought to solve the problem of parents and caregivers needing to rely on the internet to figure out what to feed their babies with food allergies. They gathered relevant information from journals, articles and books, as well as interviewed with a doctor to further strengthen the information they had gathered. They used a rule-based technique with various IF-THEN rule statements to codify the medical information into a decision-making model. The user would then register and input any allergy diagnosis their baby had. To get food recommendations, the user would put in a list of foods. The system checks if the foods are a risk based on the child's allergies. The system would then provide recipes that use the foods the child is not allergic to.

The performance of rule-based models is usually affected by the number of rules. The rule-based technique system may not handle complex or uncertain situations as well as a machine-learning-based system, as it cannot discover patterns that are not explicitly defined in the rules. Its use case is therefore very case-specific and limited (Bonaccorso, 2017; Herasevich et al., 2013).

2.5.3 Implementation of a Personalized Food Recommendation System Based On Collaborative Filtering and Knapsack Method

Thongsri et al. (2022) developed a web-based food recommendation system that offers users a selection of foods that meet their individual preferences. They applied collaborative filtering to be able to determine a new user's favourites by using the data of old users as a base. They also compounded that with the Knapsack method, which enabled them to develop food recommendations based on the daily caloric needs of the individual. The system was tested on 90 public health work operators, who were satisfied with the design and efficiency of the system.

The limitations observed with using collaborative filtering was that initial users were not getting refined results as there was no old user base from which to inform recommendations, therefore, initial users would have to provide a list of food preferences on signup, to serve as a base (Thongsri et al., 2022). The system did not take into consideration health conditions and their implications on total daily caloric requirements as well as specific food content (Rostami et al., 2022).

2.5.4 DIETOS: A Dietary Recommender System for Chronic Diseases Monitoring and Management

Agapito et al. (2018) developed DIETOS, a recommender system for nutrition content delivery to increase the quality of life for healthy individuals and those with nutritionally related lifestyle diseases. DIETOS creates health profiles by utilising the user answers to medical feedback form to deliver personalized nutritional recommendations.

DIETOS utilised the overlay profiling method of user profiling, as well as content selection for content adaptation. Dietary recommendations were achieved using guidelines specified by a medical specialist, and no specialized algorithm was utilized. DIETOS has been tested through a study with 20 chronic kidney disease patients and 20 healthy controls. The results show high accuracy in health profiling and recommendations specific to each user's health status.

DIETOS is however limited in that it does not specify the foods that go into a particular diet recommendation. For example, an average user may not know what foods make up a hypo phosphoric diet.

2.6 Summary of Related Works

Table 2.4 below summarises the related works that have been reviewed in the previous section.

Table 2.4 Summary of Related Works

Study	**Source**	**Techniques**	**Gaps**
Menu Recommendation System Using Smart Plates for Well-Balanced Diet Habits of Young Children	(Namgung et al., 2019)	IoT – Internet of Things	Practicability and Scalability concerns Small sample size (10)

Mobile Application of Food Recommendation for Allergy Baby Using Rule-Based Technique	(Shari et al., 2019)	Rule-Based Technique	Limited use cases to only predefined allergies
Implementation of a Personalized Food Recommendation System Based On Collaborative Filtering And Knapsack Method	(Thongsri et al., 2022)	Collaborative Filtering, Knapsack Method	No consideration for the health status of users. Calorie calculation only applicable to adults
DIETOS: A Dietary Recommender System for Chronic Diseases Monitoring and Management	(Agapito et al., 2018)	Content filtering	Diet recommendations do not include the particular foods that make up the diet.

2.7 Gaps Identified

Food recommendation systems are often limited in their scope and applicability. Most systems are designed for healthy adults and do not take into account the specific dietary needs of people with allergies, intolerances, or chronic diseases. Even systems that consider health requirements like those reviewed in the related works, may not offer very specific nutrition recommendations, as they often rely on general population data. This can lead to inaccurate or misleading recommendations for people with unique health needs. Food recommendation systems can also be biased, as they are often trained on data from a particular population group.

In addition, there are very few food recommendation systems tailored for child weaning. This is a critical period in a child's growth, and it is vital to guarantee that they are receiving the nutrients they require to grow and develop healthy. However, most systems are not designed to take into account the specific nutritional needs of infants and toddlers. This study proposes a system that aims to address these gaps by providing personalized nutrition recommendations for children during weaning. The system will take into account the child's individual health needs and will also be easy to use.

2.8 Conceptual Framework

The study presents a conceptual model that takes in a child's age, weight, height as user input. Using the WHO Child Growth Standards, the child will be classified as underweight, wasted or normal using a decision tree. Using feature engineering, the system will calculate the child's Total Energy Requirements (TEE), with consideration of the previous classification as underweight, overweight, wasted or normal. This calculation will be done using the Total Energy Calculation formula, provided by Butte (2001). Based on the child's age, feeding frequency will be determined using a lookup table. The lookup table will be modelled after the recommendations made by the WHO (2009).

The food database will be processed to prioritise key macronutrients and micronutrients (Carbohydrates, Fats, Proteins, Vitamin A, Iron and Zinc). The three main factors; TEE, feeding frequency and processed food data, will be fed into a diet construction module. This module will use rule-based technique to determine the foods that meet the various key nutrients and energy requirements, while also distributing them into amounts and frequencies, to build a one day meal plan.

The figure below illustrates the conceptual framework.

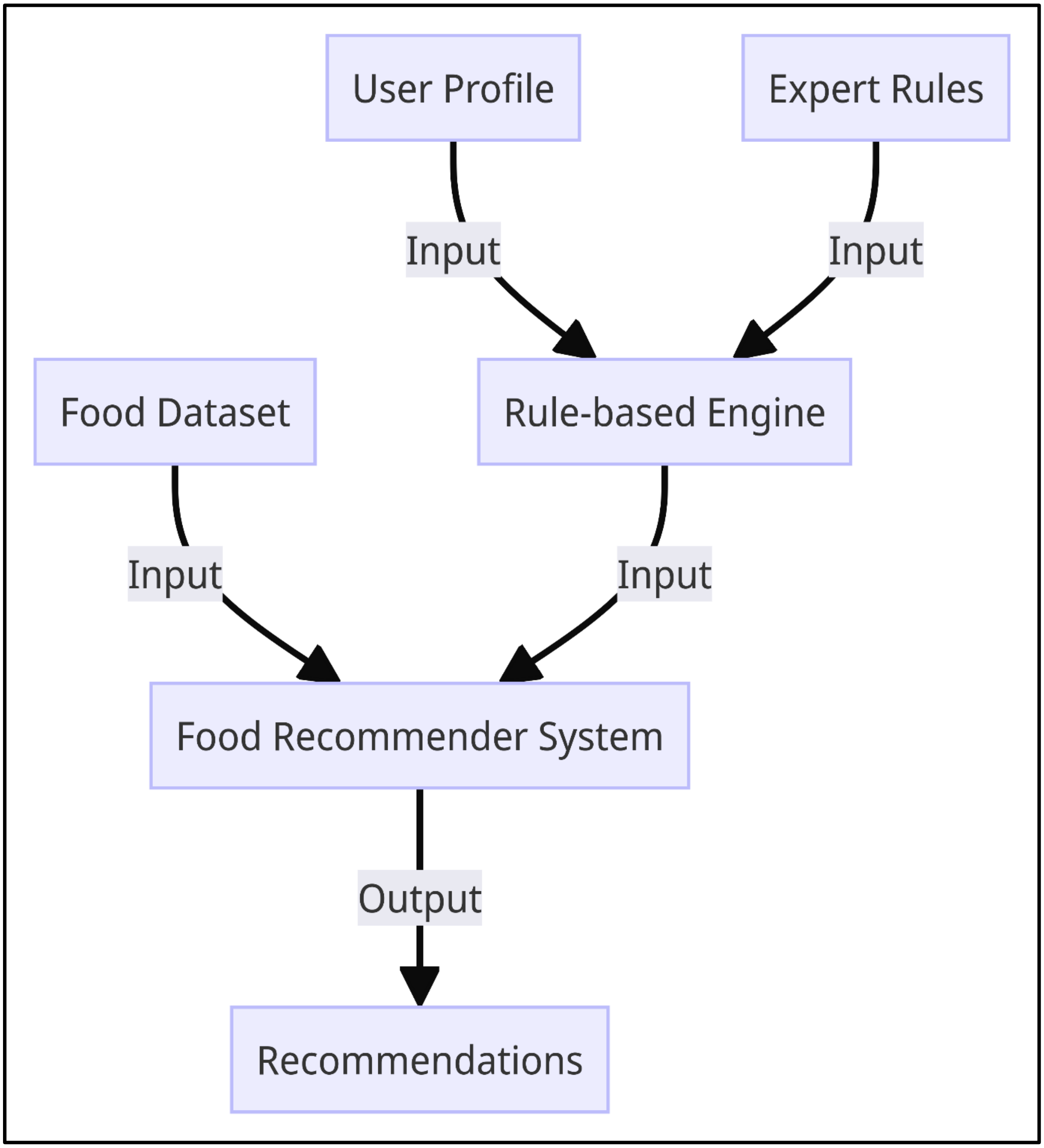

Figure 2:2 Conceptual Framework

Chapter 3: Research Methodology

3.1 Introduction

The Research Methodology chapter describes the approaches employed in this research. It outlines the research design, data collection methods, data analysis techniques, development of the rule-based model and ethical considerations.

3.2 Research Design

This study applied research to solve a real-world problem facing healthcare workers, parents and caregivers of children in the weaning stage, by building a web application that can be used by parents and caregivers to get meal plan suggestions for children at the weaning stage.

3.3 Agile Systems Development

Agile is a development methodology that emphasizes continuous iteration and improvement when creating an application model (Dybå & Dingsøyr, 2008). This approach involves breaking tasks into smaller components, each with a defined timeframe for iterative development. Agile methodology encourages ongoing feedback from end users, who can test prototypes released after each iteration and suggest improvements. Key stages in Agile development comprise planning, requirements analysis, design, building and development, and testing (Flora et al., 2014).

3.3.1 Planning

In the planning phase, the primary objective was to establish a solid foundation for the development of a rule-based food recommendation system for child weaning. This involved a comprehensive examination of the requirements, resources, and strategies essential for study success.

The study initiated this phase by identifying the specific requirements of the food recommendation system. This encompassed not only the technical aspects but also the user-centric elements. Additionally, the study defined the technical requirements, including data sources, storage, and computational resources. The study also assessed the resources required to execute the research study effectively. This included evaluating the availability of data sources, ensuring the adequacy of computational infrastructure, and outlining the skills and expertise needed for system development.

3.3.2 Requirements Analysis

At this phase, user requirements and needs were more defined and documented. Creating use-case diagrams that illustrate the interaction between users and the system helped prioritize features and functionalities that are more critical.

3.3.3 Design

At this stage, the initial designs of the user interface were created using wireframes, to illustrate how the end user will interact with the application. A usability test was carried out to ensure users can comfortably use the system. The wireframes were developed using a user interface design platform named Figma, which is comprehensive design software.

3.3.4 Building and Development

The development of the system began and was carried out in iterations. It involved writing the code that gives the system functionality and turning the initial user interface wireframes into working prototypes. Building involved two steps, building the rule-based recommendation system model, and building the web application that the end user will interact with. This phase required and utilised an integrated development environment (IDE).

3.3.5 Testing

The final code underwent unit testing, to ensure that it functioned as intended. Any necessary revisions were made to improve accuracy or functionality through further iterations.

Figure 3.1 below illustrates the iterative nature of Agile development.

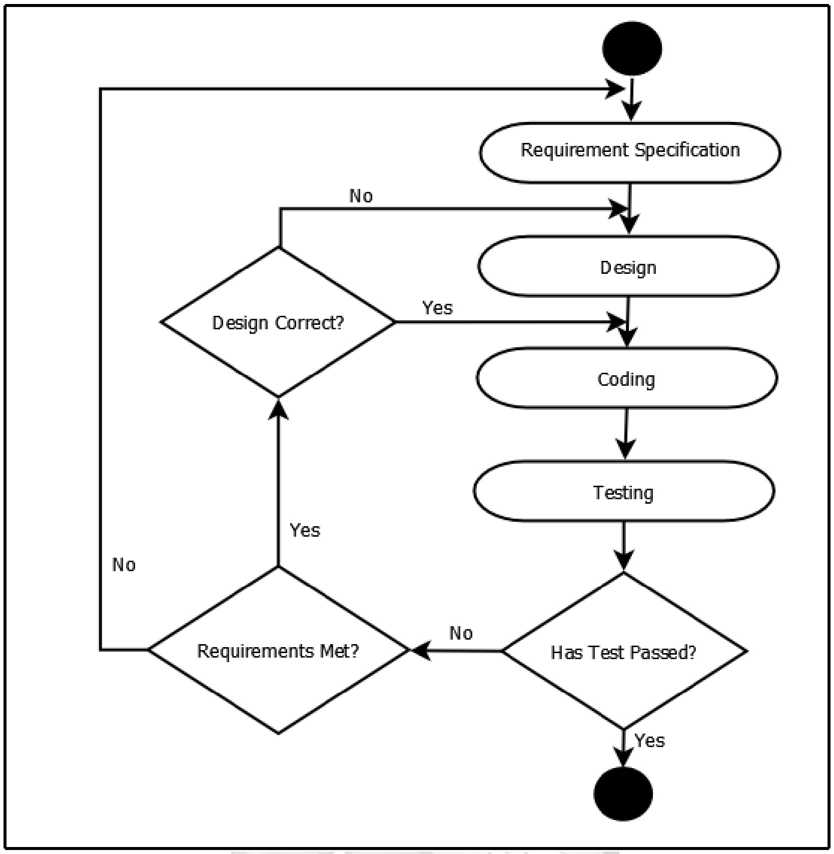

Figure 3:1 Agile Development

3.4 Data Collection

3.4.1 Food Database

For this study, secondary data was used in developing a food database for the weaning recommendation system. The food database was acquired from the Kenya Food Composition Tables (KFCT), published by the Food and Agriculture Organization (FAO) and the Government of Kenya in 2018 (FAO & Government of Kenya, 2018).

The KFCT contains a variety of foods consumed frequently in Kenya, as well as foods of public health interest that are nutrient rich. The tables include just over 500 raw and cooked foods. Some of these foods contain mixed ingredients. The foods are grouped into 15 food groups, as listed in Table 3.1 below:

Table 3.1 Food groups in KFCT 2018

Cereals and cereal products	Starchy roots, bananas and tubers
Legumes and pulses	Vegetables and vegetable products
Fruits and fruit products	Milk and dairy products
Meats, poultry and eggs	Fish and sea foods
Oils and fats	Nuts and seeds
Sugar and sweetened products	Beverages
Condiments and spices	Insects
Mixed dishes	

Analysis of the food's nutritional composition was carried out in labs in Mombasa, Kenya, as well as Thailand and Germany. Some of the data was gathered from 16 articles from research and academic institutions (FAO & Government of Kenya, 2018). The nutrient values provided are for 100grams of an edible serving of the particular food. The nutrients whose values are listed in the KFCT tables include the following listed in Table 3.2 below:

Table 3.2 Components of the KFCT 2018

Component	Unit
Energy	kJ, kcal
Water	g
Nitrogen, total	g
Protein, total	g
Fat, total	g
Cholesterol	g
Carbohydrate available, by difference	g
Fibre, total dietary	g
Ash	g

Calcium	mg
Iron	mg
Magnesium	mg
Phosphorus	mg
Potassium	mg
Sodium	mg
Zinc	mg
Selenium	µcg
Vitamin A (RAE)	µg
Vitamin A (RE)	µg
Retinol	µg
b-carotene equivalent	µg
Thiamin	mg
Riboflavin	mg
Niacin	mg
Dietary folate equivalent	µg
Folic acid	µg
Food folate	µg
Folate	µg
Vitamin B12	µg
Vitamin C	mg
Phytic acid	mg
Inositol triphosphate	mg
Inositol tetraphosphate	mg
Inositol pentaphosphate	mg
Inositol hexaphosphate	mg
Oxalate	mg

The key nutrients for the study that factored into the food recommendation system's recommendations were total energy (Kcal), total carbohydrates, total protein, total fat, iron, zinc and vitamin A. This is because these are some of the main nutrients that significantly affect childhood malnutrition and hidden hunger.

Figure 3.2 below is a snippet of the KFCT database.

Code	Food Name	Edible conversion factor	Energy (kJ)	Energy (kcal)	Water (g)	Protein (g)	Fat (g)	Carbohydrate available (g)	Fibre (g)	Ash (g)
02	**STARCHY ROOTS, TUBERS AND BANANAS**									
02003	Banana, BITA 3, dried, flour	1.00	1550	366	2.3	3.9	1.8	78.5	9.9	3.6
SD or min-max					1.5-3	3.9-3.9				3-4.2
n					2	2	1		1	2
02004	Banana, plantain, green, raw	0.50	410	97	73.6	1.4	[0.4]	20.1	3.6	0.9
SD or min-max					1.48	0	0.3-0.5			0.1
n					4	3	2		1	3
02005	Beet root, peeled, raw	0.85	184	44	86.1	2.17	0.1	6.9	3.31	1.4
SD or min-max										1.4-1.5
n					1	1	1		1	2
02021	Beet root, peeled, boiled, drained (without salt)	1.00	186	44	86	2.2	0.1	7	3.3	1.4
02023	Beet root, peeled, stewed (without salt)	1.00	174	41	86.9	2.0	0.1	6.5	3.1	1.3
02007	Cassava, root, white, peeled, raw	0.93	733	173	53.8	1.3	0.3	39.1	4.6	1
SD or min-max							0.3-0.3			
n					1	1	2		1	1
02023	Cassava, root, white, peeled, boiled, drained (without salt)	1.00	627	148	60.5	1.1	0.2	33.4	3.9	0.8
02008	Cassava, root, yellow, peeled, raw	0.95	531	126	65.7	1.6	0.2	27	4.7	0.8
n					1	1	1		1	1
02024	Cassava, root, yellow, peeled, boiled, drained (without salt)	1.00	454	107	70.7	1.4	0.2	23.1	4	0.7
02009	Potato, Irish (English), white variety, peeled, raw	0.85	447	105	72.1	2.4	0.1	22.7	1.68	1
n					1	1	1		1	1
02025	Potato, Irish (English), white variety, peeled, boiled, drained (without salt)	1.00	447	105	72.1	2.4	0.1	22.7	1.7	1
02026	Potato, Irish (English), white variety, peeled, steamed (without salt)		456	107	71.5	2.5	0.2	23.2	1.7	1
02010	Radish, round, red skin, raw	0.81	64	15	94.5	0.8	0.16	1.6	2.3	0.7
n					1	1	1		1	1

Figure 3:2 Snippet of Kenya Food Composition Tables

3.4.2 Expert Rules

To ensure the food recommendation system for weaning aligns with international best practices and local recommendations, the study incorporated expert rules derived from the joint expert policies on child nutrition from the WHO, UNICEF, and FAO, along with Kenya's MOH child feeding guidelines covered in Section 2.2 and Section 2.3 of this paper. These guidelines provide comprehensive guidance on infant and young child nutrition, including specific recommendations for weaning foods and dietary patterns. By adhering to these expert-backed guidelines, the system can effectively promote healthy and age-appropriate feeding habits for weaning infants.

3.5 Developing the rule-based food recommendation system for weaning

The development of the food recommendation system for weaning follow the following steps:

3.5.1 Data Processing

Data from the Kenya Food Composition Tables was extracted and imported, to build the food database for the recommendation system. Data from the food database was assessed to remove any repetitive records and ensure standardised format and consistency. Missing data was handled using listwise deletion for rows with multiple missing values, and mean imputation for specific columns. Data cleaning also involved ensuring measurement is consistent throughout the database and converting the units data types where necessary. Key nutrient values (carbohydrates, proteins, fats, vitamin A, zinc, iron and total energy) were be extracted from the KFCT tables into the local database. Python and its libraries were used at this stage, including NumPy and Pandas.

3.5.2 Developing the Back-end

Expert recommendations and policies on child weaning were encoded into IF-THEN structured rules using Python Framework Experta. The Experta framework was developed as part of a Python backend, built using Flask and connected to the front-end using RESTful API.

3.5.3 Developing the Front end

The web application that hosts the food recommendation system and allows user interaction with the system was developed at this phase using React. React was selected as it is lightweight and allows for reusability of components.

3.5.4 Testing

Unit testing of the final web application code and food recommendation system code was done to ensure it functions as expected. Python backend code was tested using pytest, while the React frontend code was tested using Jest. The completed system was tested to ensure the integration and overall function is as expected, using Chrome Developer Tools and the Visual Studio Code debugger. For the quality of recommendations given, nutritionists and child health specialists were consulted to validate the suitability of the system and its outputs for child weaning.

3.6 Systems Requirements

Developing the food recommendation system and web application required a computer with at least 8GB of Random Access Memory (RAM) and 256GB of Solid State Drive (SSD).

The development process also required some software applications including:

i. Python and its libraries such as NumPy, Pandas
ii. Experta framework
iii. React framework
iv. Visual Studio Code
v. Chrome Browser and Developer Tools

3.7 Ethical Considerations

The food database used in the study is published by the Government of Kenya and FAO, and is made available for non-profit seeking academic and research use, provided appropriate citation is done.

As this study deals with vulnerable populations, i.e., weaning children, careful considerations of potential impacts on their health are essential. The system was developed to promote healthy eating habits. The food recommendation system requires monitoring and assessing to ensure that no potentially negative health habits are promoted by the system. Registered Nutritionists and Dietitians were consulted to review the suitability of the recommendations made by the system.

To protect sensitive health data, no personally identifiable information such as name, location or phone number will be collected by the system. All data input into the system will be non-identifiable, and will not be stored by the system.

Chapter 4: System Design and Architecture

4.1 Introduction

This chapter covers system analysis, design, and architecture. It details the functional and non-functional system requirements, as well as the system architecture as informed by the contextual framework. A use-case diagram illustrating user interaction with the web application is also covered. A sequence diagram illustrating visually the interactions between components in the system is also developed in this chapter. These were modelled using Universal Modelling Language (UML). Finally, wireframes of the web application were developed to outline the user interface design and test the user experience.

4.2 Requirements Analysis

This section describes the system requirements as informed by the research objectives and literature review. They have been divided into two, functional requirements and non-functional requirements.

4.2.1 Functional Requirements

Functional requirements outline the specific actions or tasks that the system must be able to accomplish to meet the needs of its users (Sommerville, 2016). For the food recommendation system for weaning, the functional requirements include the following.

i. The system should allow the user to input the child's weight, height and age.
ii. The system should correctly capture the user's input and post them to the backend.
iii. The system should fetch the rule-based model's recommendations from the backend.
iv. The system should display to the user their nutritional feedback.
v. They system should display to the user the food recommendations made for weaning of the child based on their input.

4.2.2 Non-Functional Requirements

Non-functional requirements define aspects of the system's quality, usability, performance, security, and other characteristics that are not directly related to its functionality (Sommerville, 2016). The non-functional requirements for the food recommendation system for weaning include:

i. User friendly – the web application should have a simple and intuitive user interface that is easy to navigate for users with limited technical proficiency.
ii. Mobile friendly – the web application should be accessible and usable on mobile devices, and the user experience should be seamless on mobile devices.
iii. Performance – the system should provide food recommendations for weaning within 5 seconds of user input.
iv. Security – the system should not collect sensitive medical information or personally identifiable information from its users.
v. Maintainability - the system's codebase should be well-documented and organized to aid ongoing maintenance and updates.

4.3 System Architecture

Figure 4.1 below is a System Architecture diagram which provides and overview of the system. This system centres on a rule-based engine designed to simplify decision-making and produce food recommendations for weaning. The process begins with user input, where the user keys in the child’s anthropometrics into a web application. The application captures this input and communicates it to the rule-based engine contained in the application backend. The engine, equipped with these encoded expert rules, processes the user input and applies the encoded logic to generate tailored recommendations. The system then makes food recommendations based on this inferences, and the foods recommended are obtained from the food composition database.

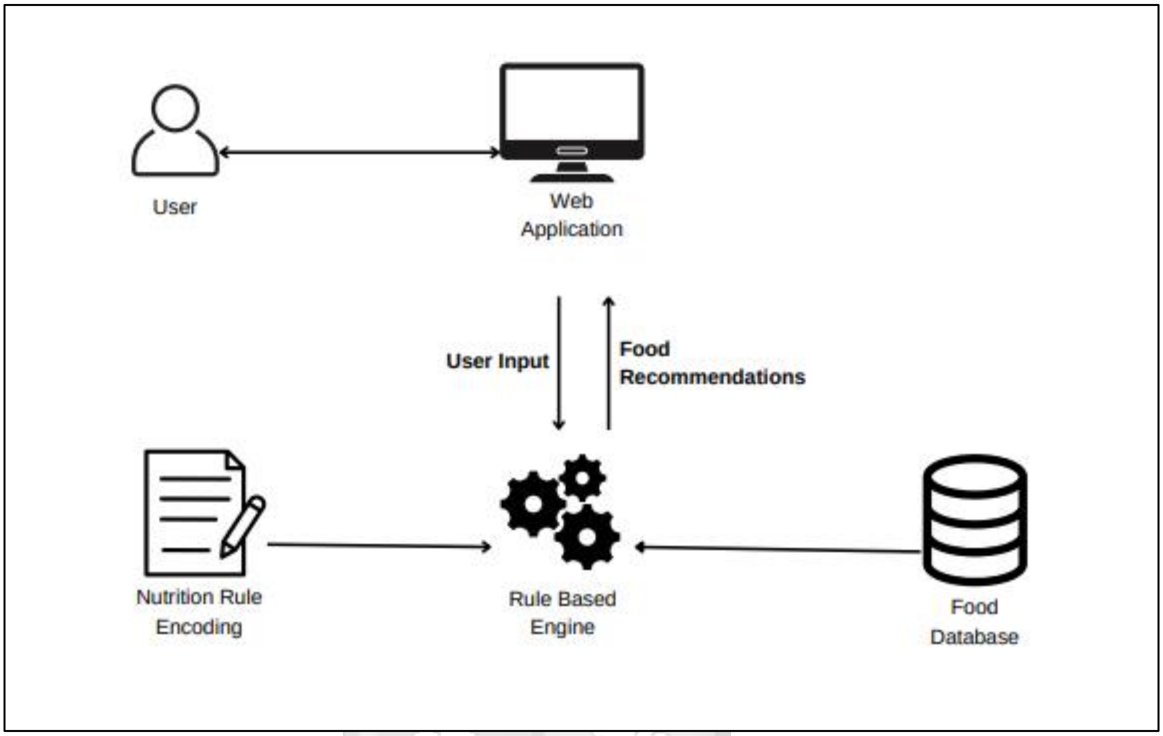

Figure 4:1 System Architecture

4.4 Use-Case Diagram

A use-case diagram is a type of behavioural diagram in the Unified Modelling Language (UML) that offers a graphical depiction of how a system interacts with its external users (known as actors) to achieve specific goals or use cases (Nishadha, 2022). Figure 4.2 illustrates the Use-Case Diagram for the web-based food recommendation system for weaning.

The System Administrator is one of two main actors for this system. The admin is responsible for developing the user interface through which the user will interact with the system. The initial step involves designing the interface that users will interact with to provide child metrics and receive food recommendations. The user interface includes features to input the child's age, weight and height. The admin establishes a set of rules that govern the food recommendations, informed by expert knowledge on child nutrition. These rules consider factors like the child's age and nutritional needs. The rules established are translated into a format that the system's rule-based engine can understand and process in the *Encode Nutrition Rules* use case. The *Upload Food Database* use case is where a comprehensive database containing information on various Kenyan foods is uploaded into the system.

In the *Input Child Metrics* use case, the primary actor is the parent or caregiver. Parents or caregivers will input data regarding the child's anthropometric measurements, into the web application. This data includes the child's age, weight and height, and will be used to determine the child's caloric requirements, in order to establish the amount and frequency of meals needed, as well as the specific proportions of vital nutrients needed in the meals. Once the user enters the child's metrics, the system queries the rule-based engine. The engine takes into account the child's information and retrieves relevant recommendations from the food database. These recommendations are presented to the user through the system's interface.

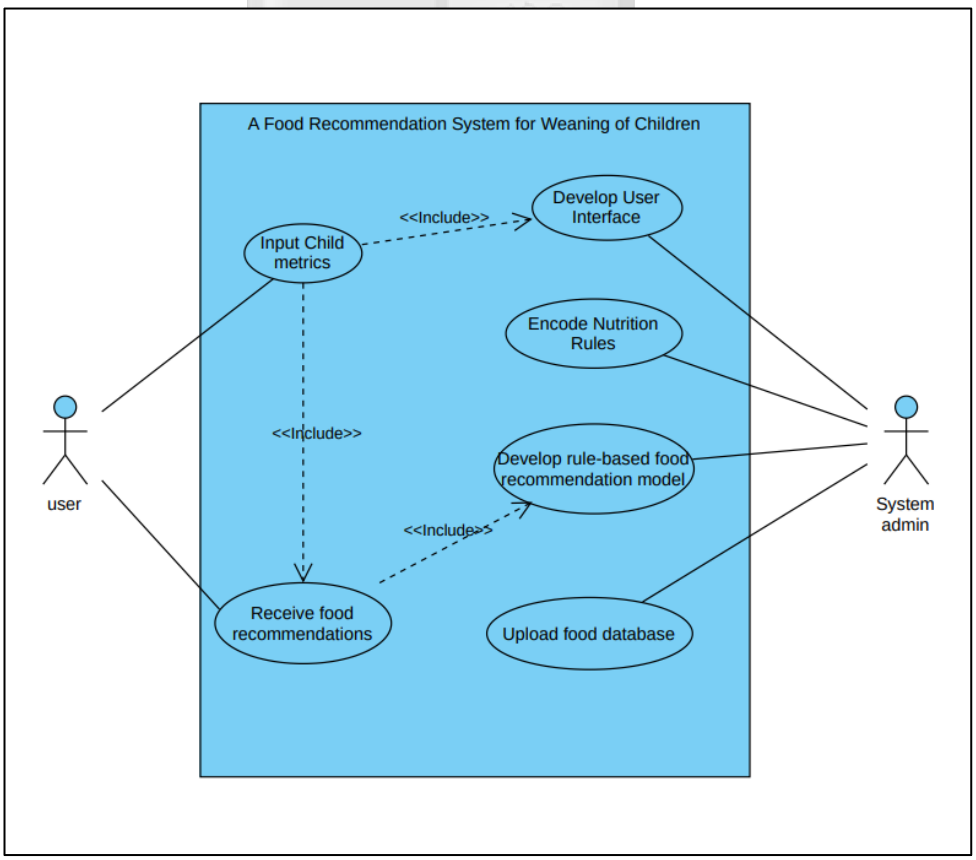

Figure 4:2 Use-Case Diagram

4.5 System Sequence Diagram

A sequence diagram is a type of interaction diagram in the Unified Modelling Language (UML) that visually exhibits how processes or objects interact with each other in a time-ordered sequence. It shows the flow of interactions between actors or components as they work together to achieve a specific goal or outcome (Sommerville, 2016). Figure 4.3 below illustrates the system sequence diagram for the food recommendation system. The sequence diagram is informed by the use case diagram illustrated in Figure 4.2.

The process initiates with the user, acting as a parent or caregiver, entering child-metrics via the web based user interface. The user interface then transmits this data to the backend system through an API (Application Programming Interface). APIs act as intermediaries that facilitate communication between different software applications. In this instance, the API relays the user-provided child metrics to the backend system for processing.

Upon receiving the data through the API, the backend system processes it and transmits it to the rule-based engine. The rule engine then leverages the encoded rules to analyse the child's metrics and generates appropriate food recommendations. These recommendations include specific food types, portion sizes, or feeding schedules tailored to the child's developmental stage and nutritional requirements.

The backend system receives the generated recommendations from the rule engine and transmits them back to the user interface. The user interface then presents these recommendations to the user for their consideration and implementation into the child's weaning process.

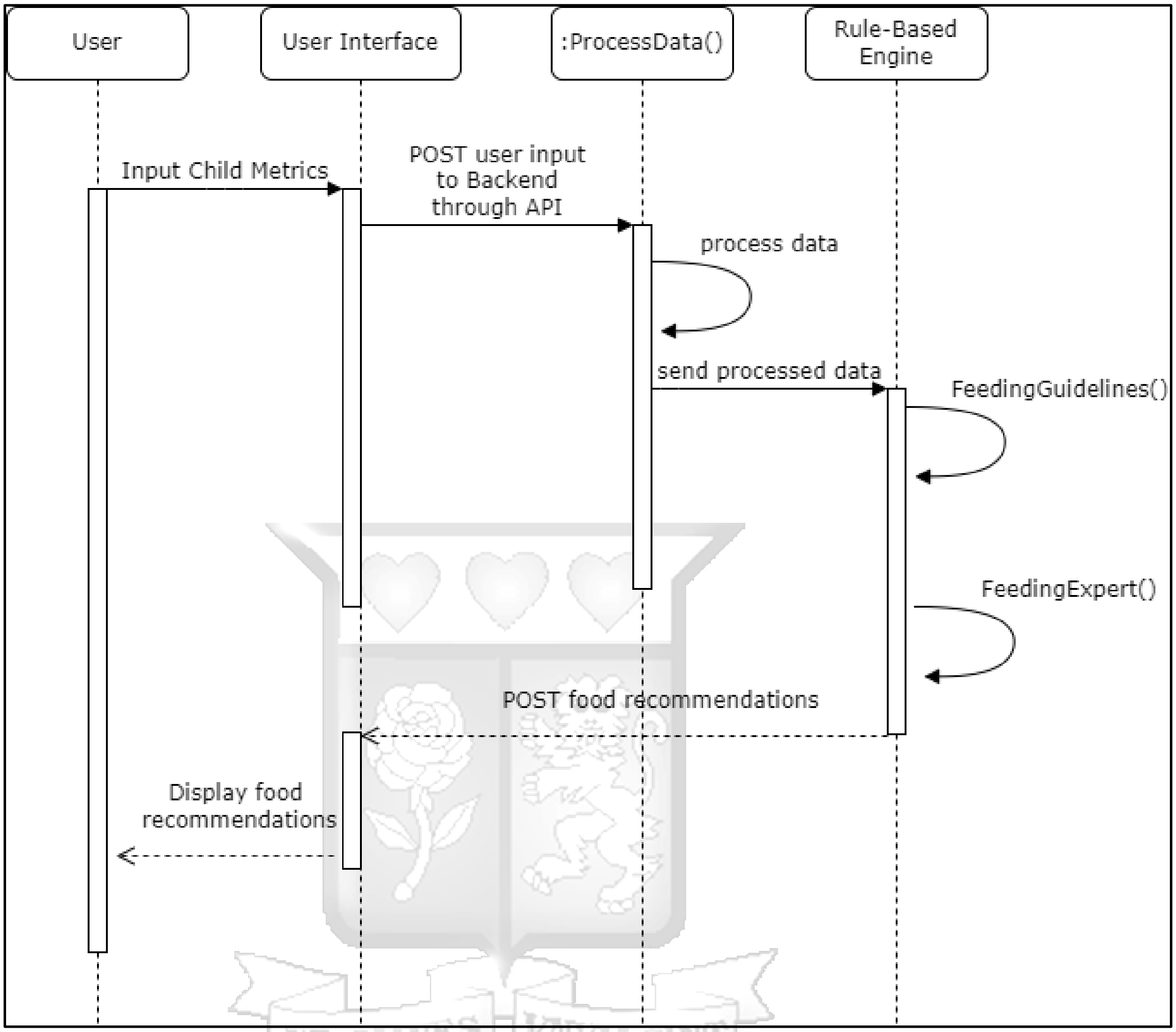

Figure 4:3 Sequence Diagram

4.6 Wireframe of Web Application

The Figure 4.4 below show the web application's wireframes, with emphasis on mobile responsiveness as it is expected that most users will access the website through their phones. Figure 4.5 shows the system in a larger device view, such as a laptop or tablet device.

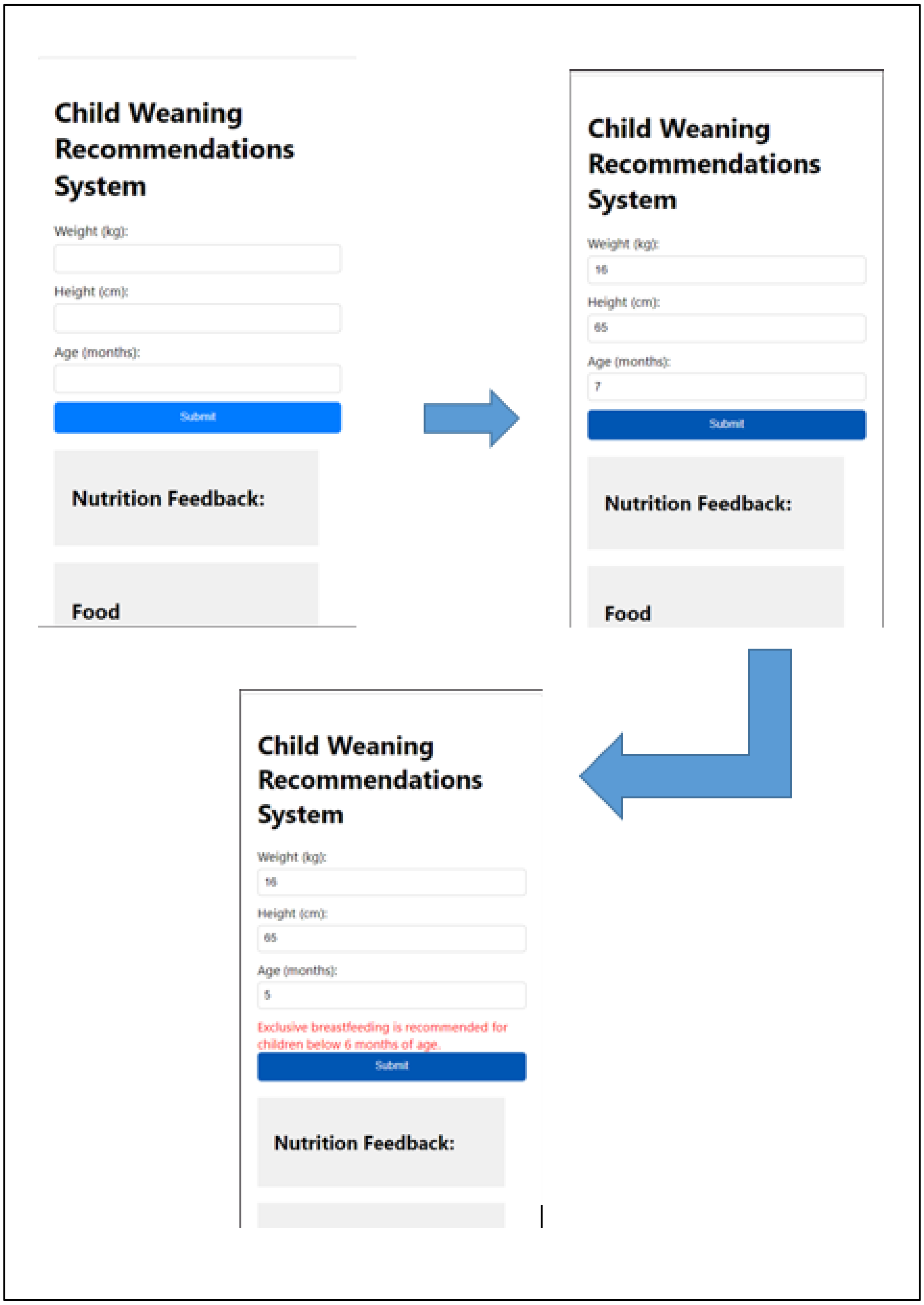

Figure 4:4 Mobile-responsive wireframes

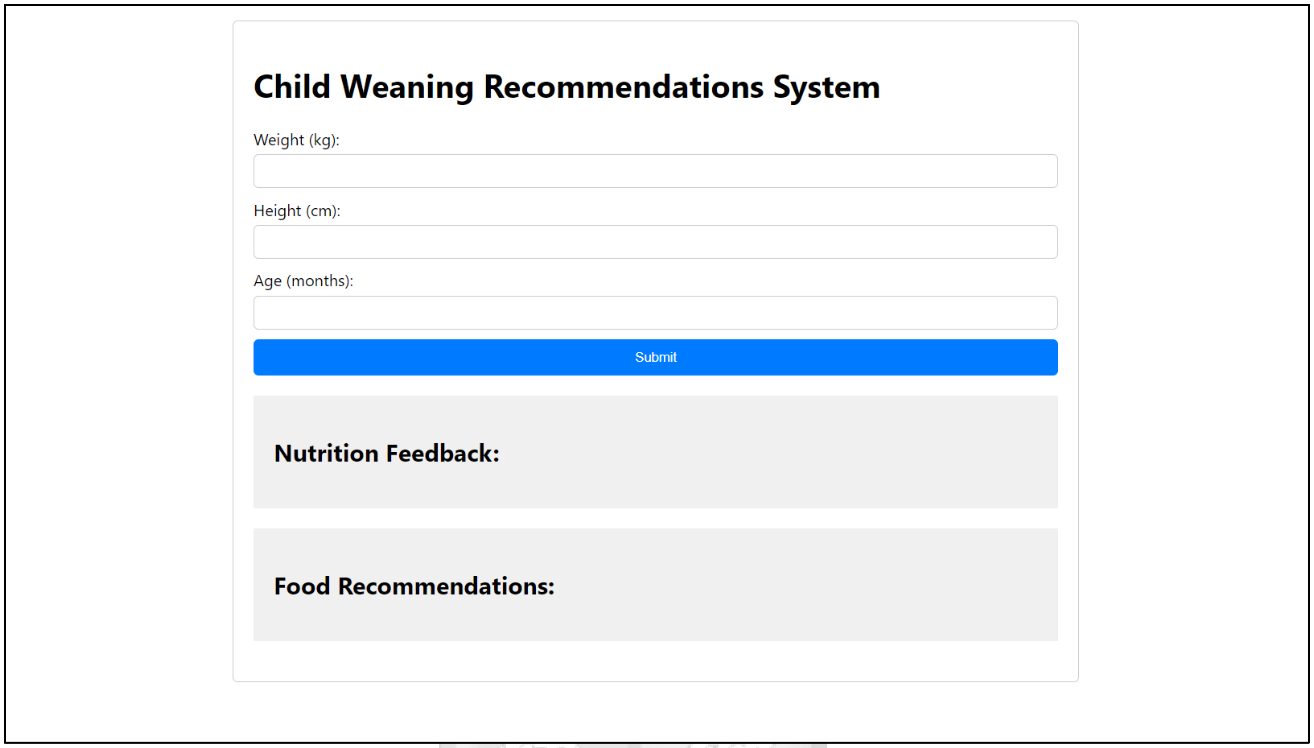

Figure 4:5 Wireframe of larger device screen

Chapter 5: System Implementation and Testing

5.1 Introduction

This chapter details how the food recommendation system for weaning was built and tested. The building and development phase of the study's agile approach focused on building the rule-based recommendation system in the first stage, and the full stack web application user interface in the second stage. The testing phase of the agile approach focused on testing the functionality of the completed prototype by testing the usability and functionality of the site, as well as error handling and input validation.

5.2 System Implementation

This study utilised the agile methodology to develop the food recommendation system for weaning of children using iterative steps. The steps followed included planning, requirements analysis, design, building and development, and concluded with testing. These steps are discussed in detail in Section 3.3 of this document.

The system is composed of a rule-based food recommendation model that is built using Python and its framework Experta. Experta is a framework designed specifically for encoding rules that are in IF-THEN formats. The rule-based model is contained in Python backend that was developed using Flask mini-web framework. The user interacts with a simplified web-based user interface that is built using React. React is a JavaScript-based library that is built for developing reactive websites. To connect to the Python backend from a JavaScript/React frontend, the system applies a RESTful web API.

5.2.1 Development Environment

To develop the system, the following hardware environment was utilised:

i. HP EliteBook 840 G3 x64-based PC
ii. Intel(R) Core(TM) i5-6300U CPU @ 2.40GHz 2.50 GHz Processor
iii. 8GB RAM
iv. 256 GB SSD

The software environment included the following tools and components.

i. Microsoft Visual Studio Code IDE
ii. Python version 3.8.10
iii. NumPy version 1.24.4
iv. Pandas version 2.0.3
v. Experta version 1.9.4
vi. Flask version 3.0.2
vii. React version 18.2.0
viii. Cascading Style Sheets (CSS)

5.2.2 Data Pre-processing

The food database used in this study was adapted from the Kenya Food Composition Tables 2018. To pre-process the database, the study used NumPy and Pandas python libraries. Pandas was used to load the data from the excel sheet, as well as to isolate the columns identified in Section 2.3 as being relevant to the study.

Missing values were handled using two different techniques, mean imputation and zero imputation. For columns Vitamin A-RAE and Vitamin A-RE, zero imputation was used due to the columns having a wide distribution of values, making it inappropriate to use mean imputation, as it would have led to skewed data. The code below illustrates the implementation of handling missing values for the two Vitamin A columns.

```
def preprocess_vitamin_a(df):
    """Replace non-numeric entries in 'Vit A-RAE (mcg)' and 'Vit A-RE (mcg)' with NaN."""
    df['Vit A-RAE (mcg)'] = df['Vit A-RAE (mcg)'].apply(clean_and_convert)
    df['Vit A-RE (mcg)'] = df['Vit A-RE (mcg)'].apply(clean_and_convert)
    return df
```

Figure 5:1 Pre-processing Vitamin A values

```
def handle_missing_values(df):
    """Handles missing values in the dataset."""
    df = preprocess_vitamin_a(df)
    df['Vit A-RAE (mcg)'] = df['Vit A-RAE (mcg)'].fillna(0)
    df['Vit A-RE (mcg)'] = df['Vit A-RE (mcg)'].fillna(0)
    df = impute_conversion_factor(df)
    return df
```

Figure 5:2 Code implementation for Zero Imputation

Missing values in the Edible Conversion factor column were handled using Mean Imputation. The food items were grouped into food groups, and mean values for the Edible Conversion factor were calculated within the food groups. The code below illustrates the implementation of mean imputation done in this study.

```
def impute_conversion_factor(df):
    """Fills missing values in 'Edible conversion factor' using the mean within each food group."""
    for food_group, group_df in df.groupby('Food_group_code'):
        group_df = group_df.iloc[2:]
        mean_factor = group_df['Edible conversion factor'].mean(skipna=True)
        mean_factor = round(mean_factor, 1)
        mask = (df['Food_group_code'] == food_group) & (df.index >= 2) & (df['Edible conversion
        factor'].isna())
        df.loc[mask, 'Edible conversion factor'] = mean_factor
    return df
```

Figure 5:3 Code Implementation for Mean Imputation

Following the pre-processing, the food database had now been converted into CSV files grouped into food groups. These processed data was now ready to be loaded and used in the rule-based food recommendation model. The full code used in the pre-processing of the food database can be found in Appendix C.

Elementary exploratory data analysis was carried out to gain an understanding of the characteristics of the food database, using seaborn and matplotlib. Table 5.1 below lists the results of the summary statistics exploration of the food database.

Table 5.1 Summary Statistics of Food Composition Database

	Edible con	Energy (kc	Protein (g)	Fat (g)	Carbohydr	Fe (mg)	Zn (mg)	Vit A-RAE (	Vit A-RE (mcg)
count	517	658	658	658	658	658	657	658	658
mean	0.896344	180.3691	8.79038	8.013526	16.04848	3.350593	1.235477	360.818	390.9757
std	0.185277	169.7271	9.574824	16.67632	19.34271	6.029152	1.558759	2762.859	2788.714
min	0.23	0	0	0	0	0	0	0	0
25%	0.86	60	2	0.3	2.2	0.6	0.3	0	0
50%	1	121	5	1.5	8.65	1.5	0.68	8	9.5
75%	1	273.5	12.65	7.4	22.7	3.175	1.45	45	58.75
max	1	900	71.8	100	100	62.9	16	38100	38100

5.2.3 Rule-based Model Development

Developing the model required installation of Experta, a python library built for developing rule-based applications. Experta is a free and open-source library and was installed successfully using pip, the Python package manager. Experta, however, required an older version of Python in order to run successfully. Therefore, the newer version of Python (version 3.12) had to be uninstalled, and Python 3.8.10 was installed, which was more compatible with Experta.

Child feeding recommendations and policies were acquired from the *Kenya National Clinical Nutrition and Dietetics Reference Manual* that contains nutrition recommendations for medical professionals, developed by Licensed Clinical Nutritionists. Specifically, recommendations were acquired from the section labelled *Infancy and Early Childhood*. Further recommendations were acquired from the *Infant and Young Child Feeding* guide published by the World Health Organisation.

To develop the rules for frequency of feeding and amount to be fed to a child depending on their age, the tables 'Table 8: Developmental milestones and guidelines for feeding children age 0 – 18 months', as well as 'Table 9: Quantity, variety and frequency of complementary foods', were used. This tables were adapted from the *Kenya National Clinical Nutrition and Dietetics Reference Manual*.

Using Experta, the rules were encoded into an IF-THEN format that took in the child's age and determined how frequently they should be fed, and approximately how much food per meal they should be fed. The code below illustrates the Experta implementation of the feeding frequency rules.

```python
from experta import *

class FeedingExpert(KnowledgeEngine):

    @Rule(FeedingGuideline(age="6-8 months"))
    def feed_6_to_8_months(self):
        self.declare("6-8 months: Introduce thick porridge, mashed or pureed foods")
        self.declare("Frequency: 2-3 meals a day, frequent breastfeeding")
        self.declare("Amount: 2-3 tablespoons to half a 250 ml cup")

    @Rule(FeedingGuideline(age="9-11 months"))
    def feed_9_to_11_months(self):
        self.declare("9-11 months: Introduce finely chopped, diced or mashed foods")
        self.declare("Frequency: 3-4 meals a day, 1-2 snacks")
        self.declare("Amount: half to three quarters of a 250ml cup")

    @Rule(FeedingGuideline(age="12-23 months"))
    def feed_12_to_23_months(self):
        self.declare("12-23 months: Introduce chopped into small pieces or mashed if needed")
        self.declare("Frequency: 3-4 meals a day, 1-2 snacks")
        self.declare("Amount: three quarters to full 250ml cup")

    def get_recommendations(self, age_in_months):
        self.reset()
        if 6 <= age_in_months <= 8:
            self.declare(FeedingGuideline(age="6-8 months"))
        elif 9 <= age_in_months <= 11:
            self.declare(FeedingGuideline(age="9-11 months"))
        elif 12 <= age_in_months <= 23:
            self.declare(FeedingGuideline(age="12-23 months"))
        self.run()
        return '\n'.join(self.facts)
```

Figure 5:4 Feeding Frequency Code Implementation

To determine the specific macronutrient needs for the child, the system takes in the child's, weight and based on their age and Recommended Daily Allowance (RDA) of calories and proteins, calculates and determines the amount of carbohydrates, fats and proteins the child needs in their meal plan. The calculations were informed by the RDA values identified in Section 2.3 of this study. Figure 5.5 below demonstrates the code applied to calculate the macronutrient amounts in grams. The code is implemented in Python.

```python
rda_data = {
    "6-8 months": {"calories": (90, 110), "protein": 2.0},
    "9-11 months": {"calories": (100, 105), "protein": 1.8},
    "12-23 months": {"calories": (100, 105), "protein": 1.5},
}

def calculate_rda(rda_data, age_range):
    """Calculates the approximate RDA for calories and protein."""
    calories_range = rda_data[age_range]["calories"]
    protein = rda_data[age_range]["protein"]
    return {"calories": (calories_range[0] + calories_range[1]) / 2, "protein": protein}

def calculate_nutrient_requirements(age_range, weight):
   rda = rda_data[age_range]
   mean_calories = (rda['calories'][0] + rda['calories'][1]) / 2
   calories = weight * mean_calories
   protein = weight * rda['protein']
   protein_calories = protein * 4  # PRO = 4kcal/g

   # Percentages for carbs(50%)/fats(30%)
   target_carb_ratio = 0.5
   target_fat_ratio = 0.3

   remaining_calories = calories - protein_calories
   carb_calories = remaining_calories * target_carb_ratio
   fat_calories = remaining_calories * target_fat_ratio

   carbs = carb_calories / 4 # carbs = 4kcal/g
   fats = fat_calories / 9 # fats = 9kcal/g

   return {
       "calories": calories,
       "protein": protein,
       "carbs": carbs,
       "fats": fats
   }
```

Figure 5:5 Macronutrient Requirements Calculations in Python

The macronutrient requirements, which are in grams, were captured by an Experta class named 'NutritionRecommendation' as demonstrated in Figure 5.6 below. This class then utilises the values in grams to determine the appropriate foods to recommend in the meal plan from the provided comprehensive food database, and ensures that these foods add up to the Daily requirements of the child.

```python
class NutritionalRecommendation(KnowledgeEngine):
    @DefFacts()
    def initial_facts(self):
        yield ChildInfo(age, weight)

    @Rule(ChildInfo(age=MATCH.age, weight=MATCH.weight))
    def calculate_requirements(self, age, weight):
        requirements = calculate_nutrient_requirements(age, weight)
        self.declare(NutrientRequirement(name="calories", value=requirements['calories']))
        self.declare(NutrientRequirement(name="protein", value=requirements['protein']))
        self.declare(NutrientRequirement(name="carbs", value=requirements['carbs']))
        self.declare(NutrientRequirement(name="fats", value=requirements['fats']))
```

Figure 5:6 Capturing Nutrient Requirements in Rule-based Engine

5.2.4 Web Application Development

The web application is a key component of the Rule-Based System as it hosts the rule-based engine and allows the end user to interact with it and gain insights and recommendations from it. To develop the web application, this study utilised React/JavaScript for the front end, and Python/Flask, for the backend.

5.2.4.1 Developing the Frontend

React was chosen due to its component-based design, enabling the creation of reusable UI elements. The performance benefits of React's virtual DOM enable smooth rendering of content, enhancing the user experience. React was installed using JavaScript's node package manager (npm). The frontend was structured into various React components, including input fields for user data entry, error handling components to provide feedback on invalid inputs, and result display components to showcase recommendations and insights.

The main component, App, manages the state and handles user interactions. Input fields are provided for users to input weight, height, and age, with corresponding state variables managed using the useState hook. Error handling components are included to display validation errors or error messages returned from the backend. Result display components present the recommendations and feedback obtained from the backend in separate sections.

User input values are captured and updated in real-time using event handlers attached to the input fields, triggering state updates via the setWeight, setHeight, and setAge functions. Upon submission of the form, the handleSubmit function is invoked, which performs input validation and sends a POST request to the backend API endpoint '/process-data' with the input data in JSON format. The backend processes the data and returns recommendations and feedback, which are then stored in the frontend state variables (recommendations and feedback) and displayed in the respective sections of the interface. Any errors encountered during data processing are captured and displayed to the user through the error state variable, ensuring a seamless and informative user experience. The full code implementation can be found in Appendix D of this document. Figure 5.7 below displays the simple and intuitive User Interface developed using React.

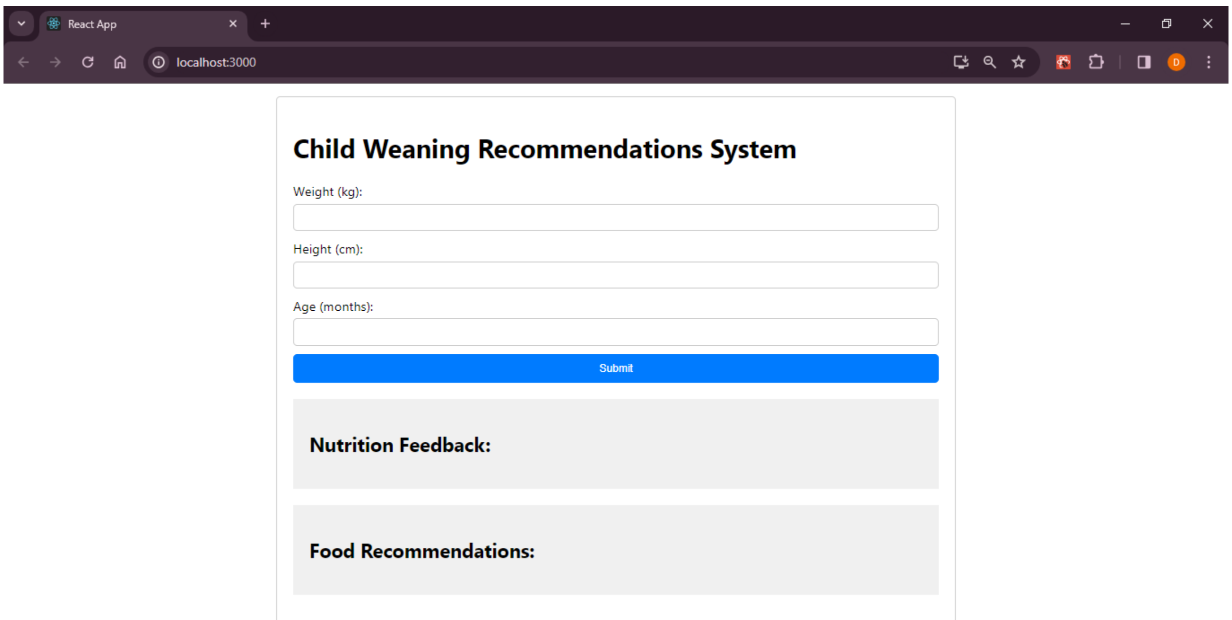

Figure 5:7 User Interface of Food Recommendation System

5.2.4.2 Developing the Backend

Flask was selected for its lightweight and flexible nature, making it ideal for building RESTful APIs to handle communication between the frontend and backend. To develop the backend, Flask was installed using PIP.

The Flask backend exposes a single API endpoint, '/process-data', which accepts POST requests for processing user data and providing recommendations. User input, consisting of weight, height, and age, is extracted from the JSON payload of the POST request.. Upon receiving a request, the backend validates the user input, ensuring that the age falls within the specified range of 6 to 23 months. If the input passes validation, the backend instantiates a FeedingExpert class and invokes its 'get_recommendations' method to retrieve feeding recommendations based on the provided age. The recommendations obtained from the expert system are then included in the response along with any additional feedback generated during the process. Any errors encountered during data processing are appropriately handled and returned as JSON responses with relevant error messages and status codes. The script can be found in Appendix E of this document.

5.3 System Testing

5.3.1 Input Validation Testing

Input validation was implemented to ensure all input fields (weight, height and age) are filled before form submission. An error message is displayed if any required field is left empty, prompting the user to provide values for all fields. Figure 5.8 below illustrates the error message displayed.

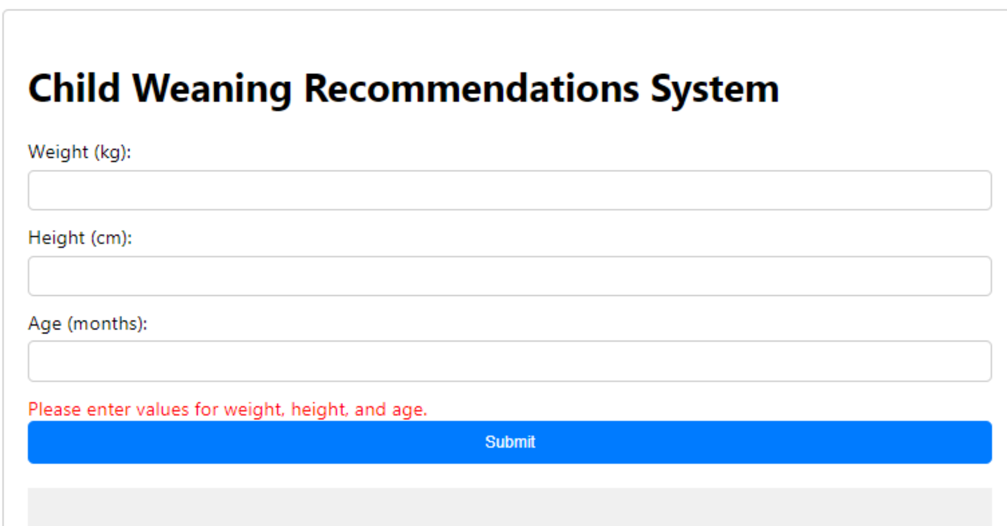

Figure 5:8 Error Message for Missing Inputs

Validation was also implemented to ensure that the age input falls within the specified age range of 6 to 23 months. For age inputs below 6 months, a reminder that exclusive breastfeeding is recommended is displayed.

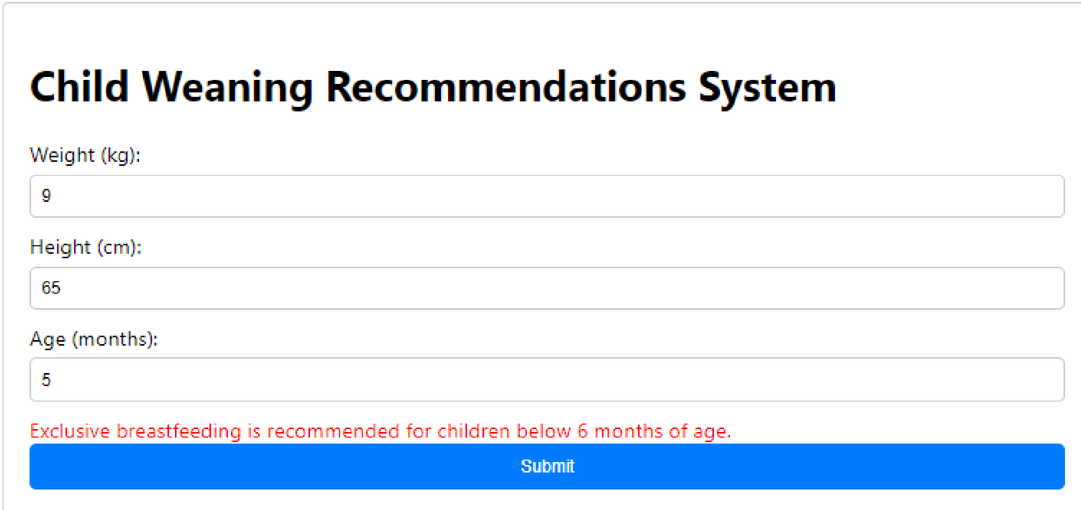

Figure 5:9 Error Message for Age below 6 Months

5.3.2 Integration Testing

During integration testing, Chrome Developer Tools and React Developer Tools, were extensively used to debug API communication issues. For instance, to test system behaviour with an unavailable backend, the server was deliberately shut down. Attempts to interact with the application resulted in network errors, clearly visible in Chrome Developer Tools (e.g., 'ERR_CONNECTION_REFUSED' in the response tab, see Figure 5.8 below). This exercise confirmed the application's ability to handle scenarios with backend unavailability.

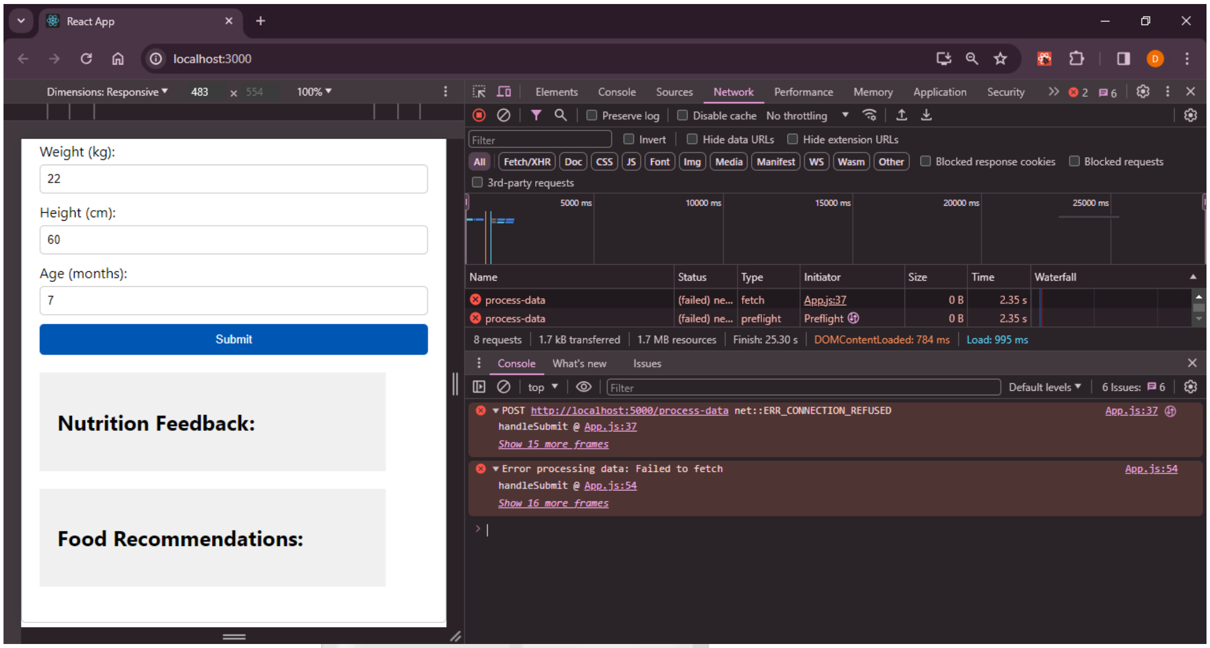

Figure 5:10 Error Connecting to Backend Server

Furthermore, when submitting a form with invalid data, the Network tab revealed a 400 Bad Request error from the backend. The response body provided details about the specific validation errors. This helped pinpoint the necessary changes for client-side validation. Another issue encountered was an error 500, indicating an internal server error on the backend. This error arose due to an issue within the server-side code or configuration, leading to the inability to fulfil requests. To address this issue, thorough investigation of server logs and debugging procedures was conducted to identify and rectify the root cause of the error. By resolving the underlying issue, the stability and reliability of the backend system were restored, ensuring seamless operation during subsequent testing phases.

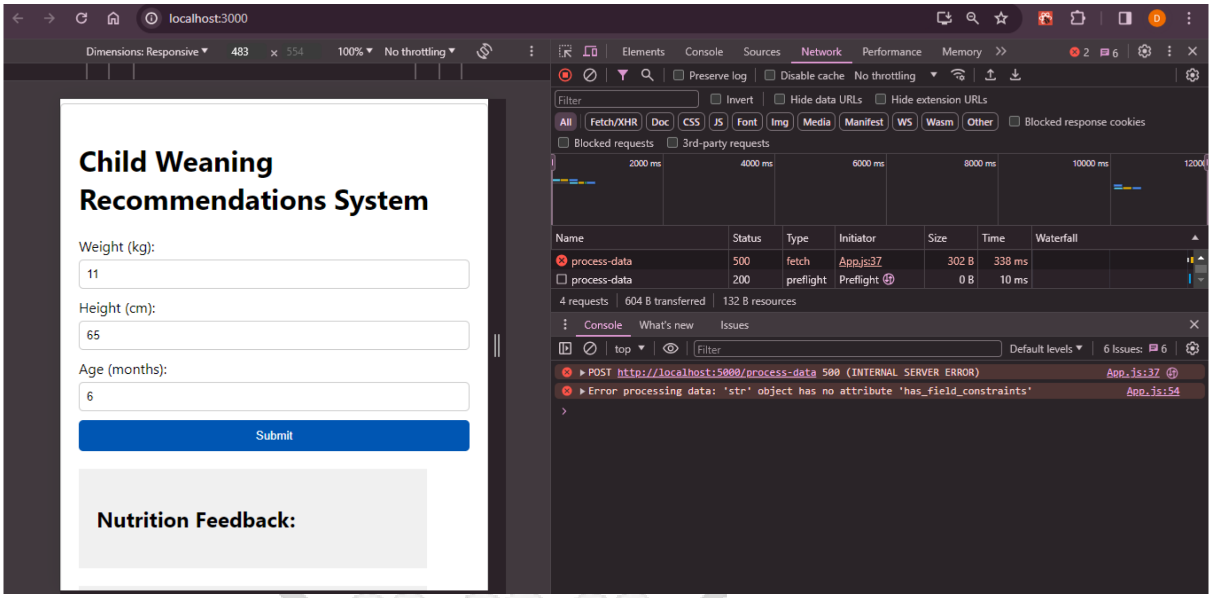

Figure 5:11 Internal Server Error

5.4 System Validation

The web application underwent in-depth validation to ensure compatibility across a range of web browsers, including Chrome, Edge, and Safari. Extensive testing was conducted to verify that the application's functionality, layout, and performance remained consistent and optimal across different browser environments. Additionally, the application was tested across various devices, including both mobile and larger screen sizes, to ensure responsiveness and adaptability to different screen resolutions. This approach ensured that users could access and interact with the application seamlessly regardless of the browser or device used.

Chapter 6: Results and Discussions

6.1 Introduction

This chapter covers the results of the rule-based food recommendation system built in Chapter 5. It reviews the research objectives and discusses how they were achieved. This study aimed to develop a food recommendation system for weaning of children in Kenya aged 6 to 23 months. The system was to be contained in a full-stack web application.

6.2 Review of Research Objectives

In reference to Section 2.3 of this research study, the first objective of the research was to define the key nutritional requirements of children in the weaning stage. Through the study of various literature, the researcher found that the key nutrients of concern included the three main macronutrients (carbohydrates, proteins and fats) and a number of micronutrients (iron, zinc, vitamin A) as discusses in Section 2.3 of the Literature Review. It was found that a nutritionally inadequate diet in childhood would have lingering long-term effects on the health of the child.

The second objective was to analyse the weaknesses of existing food recommendation systems. The various systems discussed in the Related Works section of the literature review used a variety of mechanisms such as Content Filtering, Collaborative Filtering, Rule-Based Technique and Internet of Things. The study concluded that application of Information, Communications and Technology in healthcare are playing a vital role in improving health and nutrition outcomes. The study applied Rule-Based technique to develop a child weaning food recommendation system, as covered in Section 2.4 of this research.

The third objective was to develop a food recommendation system for weaning. The system would need to be tailored to the needs of children aged 6 to 23 months and would focus on making recommendations of foods commonly eaten in Kenya. The application was built using Flask and React for the web application. A food composition database of Kenyan foods was used in making the food recommendations. Rule-based techniques was applied to encode the nutrition rules, using Python's rule-based library

Experta, which is discussed in further detail in Section 2.4 of the research study. The system was tailored with rules specific for food recommendations for child weaning.

The fourth objective was to test the effectiveness of the developed food recommendation system for weaning. Input validation tests were carried out to ensure that users input usable data and that this data is accurately captured. Integration tests were done to ensure the frontend the backend and the rule-based engine all worked well seamlessly and that users could enter input and received appropriate nutrition feedback and feeding recommendations, as covered in Section 5.3 of this study.

6.3 Advantages of the application

The developed application aids parents and caregivers in developing nutritionally diverse and adequate meal plans for their children, which in turn promotes the health and wellbeing of children. Furthermore, the application can be used by other healthcare professionals and community health workers/volunteers in facilities with few nutrition officers, to offer weaning advised to parents/caregivers.

6.4 Limitations of the application

The application focused primarily of children aged 6 to 23 months who are otherwise healthy. It therefore does not cater to children who may have significant health concerns. The application only caters to children under 6 months old, as they are presumed to be exclusively breastfeeding. Furthermore, the application does not cater to caloric and nutrient calculations for children over 2 years old. Moreover, the application relies on internet connectivity for functionality, potentially posing limitations to users in areas with limited access to the internet.

Chapter 7: Conclusions

7.1 Introduction

This research sought to develop a rule-based system targeting children aged 6 to 23 months, focusing on their nutritional needs within a healthy demographic. The goal was to create an application that offers personalised recommendations and insights tailored to this specific age group. The following subsections will delve into the outcomes of the project and offer recommendations for its adoption and potential future improvements.

7.2 Conclusion

The main objective of this study was to develop a food recommendation system for child weaning using rule-based technique. This was in response to an observed need for parents and caregivers to receive balanced and nutritionally acceptable food recommendations for their growing children. As reported in the problem statement, many young children were not receiving a minimum acceptable diet and were at risk of developing childhood malnutrition. Part of the reason for this is a lack of access to information for parents and caregivers.

The food database used was adapted from the Kenya Food Composition Tables. The database was pre-processed, key food composition columns were isolated, and the food items were grouped into 15 food groups to improve quality of recommendations. The nutrition rules were adapted from guidelines published by Kenya's Ministry of Health as well as the World Health Organisation. The system adhered to stipulated guidelines and was able to offer insights into the nutritional needs of children in the weaning stage.

7.3 Recommendations

To optimize the utilization and adoption of the rule-based system, it is recommended to integrate it into existing healthcare systems. Continued collaboration with healthcare professionals can enhance the system's credibility and ensure alignment with established nutritional guidelines. Additionally, efforts should be made to enhance accessibility, particularly in regions with limited internet connectivity, through the development of mobile applications or offline functionalities. Furthermore, user education and awareness campaigns can promote the system's usage among caregivers and parents, facilitating better nutritional management for young children.

7.4 Future Works

It is proposed to consider the integration of machine learning techniques to enhance the system's ability to adapt and evolve based on user feedback and emerging nutritional research. Additionally, the development of mobile applications tailored for accessibility in areas with limited internet access can broaden the system's reach and impact. Furthermore, potential collaborations with public health organizations or research institutions can facilitate the collection of comprehensive data sets and insights, particularly datasets on nutrition recommendations and meal plans prepared for children in the weaning stage, paving the way for advancements in paediatric nutrition science. This can also allow for the system to offer more comprehensive recommendations that consider allergies and medical conditions among other factors.

References

Abhari, S., Safdari, R., Azadbakht, L., Lankarani, K. B., Niakan Kalhori, S. R., Honarvar, B., Abhari, K., Ayyoubzadeh, S. M., Karbasi, Z., Zakerabasali, S., & Jalilpiran, Y. (2019). A Systematic Review of Nutrition Recommendation Systems: With Focus on Technical Aspects. *Journal of Biomedical Physics & Engineering*, *9*(6), 591–602. https://doi.org/10.31661/jbpe.v0i0.1248

Agapito, G., Simeoni, M., Calabrese, B., Caré, I., Lamprinoudi, T., Guzzi, P. H., Pujia, A., Fuiano, G., & Cannataro, M. (2018). DIETOS: A dietary recommender system for chronic diseases monitoring and management. *Computer Methods and Programs in Biomedicine*, *153*, 93–104. https://doi.org/10.1016/j.cmpb.2017.10.014

Bhandari, N. (2016). Infant and Young Child Feeding. *Proceedings of the Indian National Science Academy*, *82*(0). https://doi.org/10.16943/ptinsa/2016/48883

Bonaccorso, G. (2017). *Machine learning algorithms: A reference guide to popular algorithms for data science and machine learning*. Packt.

Briguglio, M., Hrelia, S., Malaguti, M., Lombardi, G., Riso, P., Porrini, M., Perazzo, P., & Banfi, G. (2020). The Central Role of Iron in Human Nutrition: From Folk to Contemporary Medicine. *Nutrients*, *12*(6), 1761. https://doi.org/10.3390/nu12061761

Cottrell, E. C., & Ozanne, S. E. (2008). Early life programming of obesity and metabolic disease. *Physiology & Behavior*, *94*(1), 17–28. https://doi.org/10.1016/j.physbeh.2007.11.017

Dybå, T., & Dingsøyr, T. (2008). Empirical studies of agile software development: A systematic review. *Information and Software Technology*, *50*(9–10), 833–859. https://doi.org/10.1016/j.infsof.2008.01.006

Faizan, U., & Rouster, A. S. (2023). *Nutrition and Hydration Requirements In Children and Adults*. StatPearls Publishing. https://www.ncbi.nlm.nih.gov/books/NBK562207/

FAO & Government of Kenya. (2018). *Kenya Food Composition Tables* (p. 254). https://www.fao.org/3/I9120EN/i9120en.pdf

Flora, H. K., V. Chande, S., & Wang, X. (2014). Adopting an Agile Approach for the Development of Mobile Applications. *International Journal of Computer Applications*, *94*(17), 43–50. https://doi.org/10.5120/16454-6199

Giarratano, J. C., & Riley, G. (2006). *Expert systems: Principles and programming* (4. ed., [repr.]). Thomson Course Technology.

Gluckman, P. D., Hanson, M. A., Bateson, P., Beedle, A. S., Law, C. M., Bhutta, Z. A., Anokhin, K. V., Bougnères, P., Chandak, G. R., Dasgupta, P., Smith, G. D., Ellison, P. T., Forrester, T. E., Gilbert, S. F., Jablonka, E., Kaplan, H., Prentice, A. M., Simpson, S. J., Uauy, R., & West-Eberhard, M. J. (2009). Towards a new developmental synthesis: Adaptive developmental plasticity and human disease. *The Lancet*, *373*(9675), 1654–1657. https://doi.org/10.1016/S0140-6736(09)60234-8

Herasevich, V., Kor, D. J., Subramanian, A., & Pickering, B. W. (2013). Connecting the dots: Rule-based decision support systems in the modern EMR era. *Journal of Clinical Monitoring and Computing*, *27*(4), 443–448. https://doi.org/10.1007/s10877-013-9445-6

Jackson, P. (1999). *Introduction to expert systems* (3. ed., [Nachdr.]). Addison-Wesley.

Julia, V., Macia, L., & Dombrowicz, D. (2015). The impact of diet on asthma and allergic diseases. *Nature Reviews Immunology*, *15*(5), 308–322. https://doi.org/10.1038/nri3830

KNBS & ICF. (2023). *Kenya Demographic and Health Survey 2022: Key Indicators Report*. KNBS (Kenya National Bureau of Statistics) and ICF (ICF International).

Koplin, J. J., Osborne, N. J., Wake, M., Martin, P. E., Gurrin, L. C., Robinson, M. N., Tey, D., Slaa, M., Thiele, L., Miles, L., Anderson, D., Tan, T., Dang, T. D., Hill, D. J., Lowe, A. J., Matheson, M. C., Ponsonby, A.-L., Tang, M. L. K., Dharmage, S. C., & Allen, K. J. (2010). Can early introduction of egg prevent egg allergy in infants? A population-based study. *Journal of Allergy and Clinical Immunology*, *126*(4), 807–813. https://doi.org/10.1016/j.jaci.2010.07.028

Kuo, A. A., Inkelas, M., Slusser, W. M., Maidenberg, M., & Halfon, N. (2011). Introduction of Solid Food to Young Infants. *Maternal and Child Health Journal*, *15*(8), 1185–1194. https://doi.org/10.1007/s10995-010-0669-5

Lopez-Barreiro, J., Garcia-Soidan, J. L., Alvarez-Sabucedo, L., & Santos-Gago, J. M. (2023). Practical Approach to Designing and Implementing a Recommendation System for Healthy Challenges. *Applied Sciences*, *13*(17), 9782. https://doi.org/10.3390/app13179782

Lowe, N. M. (2021). The global challenge of hidden hunger: Perspectives from the field. *Proceedings of the Nutrition Society*, *80*(3), 283–289. https://doi.org/10.1017/S0029665121000902

Luger, G. F., & Stubblefield, W. A. (1993). *Artificial intelligence: Structures and strategies for complex problem solving* (2nd ed). Benjamin/Cummings Pub. Co.

Masr, N., Sultan, Y. A., Akkila, A. N., Almasri, A., Ahmed, A., Mahmoud, A. Y., Zaqout, I., & Abu-Naser, S. S. (2019). Survey of Rule-Based Systems. *International Journal of Academic Information Systems Research (IJAISR)*, *3*(7), 1–22.

Ministry of Health. (2010). *Kenya National Clinical Nutrition and Dietetics Reference Manual* (First). Republic of Kenya.

Ministry of Health. (2018). *Kenya Nutrition Action Plan (KNAP) 2018-2022*. Government of Kenya.

Namgung, K., Kim, T.-H., & Hong, Y.-S. (2019). Menu Recommendation System Using Smart Plates for Well-balanced Diet Habits of Young Children. *Wireless Communications and Mobile Computing*, *2019*, 1–10. https://doi.org/10.1155/2019/7971381

Neapolitan, R. E., & Jiang, X. (2018). *Artificial Intelligence: With an Introduction to Machine Learning* (2nd ed.). Chapman and Hall/CRC. https://doi.org/10.1201/b22400

Nishadha. (2022, October 19). *Use Case Diagram Tutorial (Guide with Examples) | Creately*. https://creately.com/guides/use-case-diagram-tutorial/

Ogidan, E. T., Dimililer, K., & Ever, Y. K. (2018). Machine Learning for Expert Systems in Data Analysis. *2018 2nd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, 1–5. https://doi.org/10.1109/ISMSIT.2018.8567251

Rehman, F., Khalid, O., Haq, N. ul, Khan, A. ur R., Bilal, K., & Madani, S. A. (2017). Diet-Right: A Smart Food Recommendation System. *KSII Transactions on Internet and Information Systems*, *11*(6). https://doi.org/10.3837/tiis.2017.06.006

Ricci, F. (Ed.). (2011). *Recommender systems handbook*. Springer.

Romero-Velarde, E., Villalpando-Carrión, S., Pérez-Lizaur, A. B., Iracheta-Gerez, Ma. D. L. L., Alonso-Rivera, C. G., López-Navarrete, G. E., García-Contreras, A., Ochoa-Ortiz, E., Zarate-Mondragón, F., López-Pérez, G. T., Chávez-Palencia, C., Guajardo-Jáquez, M., Vázquez-Ortiz, S., Pinzón-Navarro, B. A., Torres-Duarte, K. N., Vidal-Guzmán, J. D., Michel-Gómez, P. L., López-Contreras, I. N., Arroyo-Cruz, L. V., … Pinacho-Velázquez, J. L. (2016). Guidelines for complementary feeding in healthy infants. *Boletín Médico Del Hospital Infantil de México (English Edition)*, *73*(5), 338–356. https://doi.org/10.1016/j.bmhime.2017.11.007

Roohani, N., Hurrell, R., Kelishadi, R., & Schulin, R. (2013). Zinc and its importance for human health: An integrative review. *Journal of Research in Medical Sciences: The Official Journal of Isfahan University of Medical Sciences*, *18*(2), 144–157.

Rostami, M., Muhammad, U., Forouzandeh, S., Berahmand, K., Farrahi, V., & Oussalah, M. (2022). An effective explainable food recommendation using deep image clustering and community detection. *Intelligent Systems with Applications*, *16*, 200157. https://doi.org/10.1016/j.iswa.2022.200157

Russell, S. J., Norvig, P., & Davis, E. (2010). *Artificial intelligence: A modern approach* (3rd ed). Prentice Hall.

Shari, A. A., Pajar, N. A., Sabri, N., Mohd Noordin, M. R., Ishak Zainudin, F. M., Shari, A. S., & Ahmad, A. (2019). Mobile Application of Food Recommendation For Allergy Baby Using Rule-Based Technique. *2019 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS)*, 273–278. https://doi.org/10.1109/I2CACIS.2019.8825026

Soliman, A., De Sanctis, V., Alaaraj, N., Ahmed, S., Alyafei, F., Hamed, N., & Soliman, N. (2021). Early and Long-term Consequences of Nutritional Stunting: From Childhood to Adulthood: Early and Long-term Consequences of Nutritional Stunting. *Acta Bio Medica Atenei Parmensis*, *92*(1), 11346. https://doi.org/10.23750/abm.v92i1.11346

Sommerville, I. (2016). *Software engineering* (Tenth edition). Pearson.

Sorrenti, S., Baldini, E., Pironi, D., Lauro, A., D'Orazi, V., Tartaglia, F., Tripodi, D., Lori, E., Gagliardi, F., Praticò, M., Illuminati, G., D'Andrea, V., Palumbo, P., & Ulisse, S. (2021). Iodine: Its Role in Thyroid Hormone Biosynthesis and Beyond. *Nutrients*, *13*(12), 4469. https://doi.org/10.3390/nu13124469

Stevens, G. A., Bennett, J. E., Hennocq, Q., Lu, Y., De-Regil, L. M., Rogers, L., Danaei, G., Li, G., White, R. A., Flaxman, S. R., Oehrle, S.-P., Finucane, M. M., Guerrero, R., Bhutta, Z. A., Then-Paulino, A., Fawzi, W., Black, R. E., & Ezzati, M. (2015). Trends and mortality effects of vitamin A deficiency in children in 138 low-income and middle-income countries between 1991 and 2013: A pooled analysis of population-based surveys. *The Lancet Global Health*, *3*(9), e528–e536. https://doi.org/10.1016/S2214-109X(15)00039-X

Thongsri, N., Warintarawej, P., Chotkaew, S., & Saetang, W. (2022). Implementation of a personalized food recommendation system based on collaborative filtering and knapsack method. *International Journal of Electrical and Computer Engineering (IJECE)*, *12*(1), 630. https://doi.org/10.11591/ijece.v12i1.pp630-638

UNICEF. (2018). *Situation Analysis of Children and Women in Kenya 2017*.

WHO. (2021, June 9). *Infant and Young Child Feeding*. https://www.who.int/news-room/fact-sheets/detail/infant-and-young-child-feeding

WHO, & UNICEF (Eds.). (2003). *Global strategy for infant and young child feeding*. WHO.

Appendices

7.5 Appendix A: Similarity Report

152445 Dawn Ndemo Dissertation.pdf

ORIGINALITY REPORT

6%	7%	3%	4%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	su-plus.strathmore.edu Internet Source	3%
2	thesai.org Internet Source	1%
3	www.fao.org Internet Source	<1%
4	guidelines.health.go.ke:8000 Internet Source	<1%
5	ir.busitema.ac.ug Internet Source	<1%
6	Submitted to University of Hertfordshire Student Paper	<1%
7	www.researchgate.net Internet Source	<1%
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11	Submitted to International Health Sciences University Student Paper	<1%
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7.6 Appendix B: Ethical Clearance

Strathmore
UNIVERSITY

04 March 2024

Dear Ms. Dawn Ndemo

RE: A Food Recommendation System for Weaning

This is to inform you that SU-ISERC has reviewed and Approved your above research proposal. Your application reference number is SU-ISERC1924/23. The approval period is valid for exactly **one year** from today.

This approval is subject to compliance with the following requirements:

1. Only approved documents including (informed consents, study instruments, MTA) will be used.
2. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
3. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
4. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
5. Clearance for the export of biological specimens must be obtained from relevant institutions.
6. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
7. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from the National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

7.7 Appendix C: Food Database Pre-processing Script

```
import os
import openpyxl
import pandas as pd
import numpy as np

def get_food_group_code(code):
    """Extracts the food group code from a 4-digit or 5-digit code."""
    code_str = str(code)
    if len(code_str) == 4:
        return code_str[0]
    else:
        return code_str[:2]

def clean_and_convert(value):
    """Clean and convert values to numeric, handling special cases."""
    try:
        return float(value)
    except ValueError:
        if '[' in value:
            cleaned_value = ''.join(char for char in value if char.isdigit() or char in ['.',
'-'])
            return float(cleaned_value) if cleaned_value else np.nan
        elif value.lower() in ['-', 'tr']:
            return np.nan
        else:
            return np.nan

def preprocess_vitamin_a(df):
    """Replace non-numeric entries in 'Vit A-RAE (mcg)' and 'Vit A-RE (mcg)' with NaN."""
    df['Vit A-RAE (mcg)'] = df['Vit A-RAE (mcg)'].apply(clean_and_convert)
    df['Vit A-RE (mcg)'] = df['Vit A-RE (mcg)'].apply(clean_and_convert)
    return df

def impute_conversion_factor(df):
    """Fills missing values in 'Edible conversion factor' using the mean within each food
group."""
    for food_group, group_df in df.groupby('Food_group_code'):
        group_df = group_df.iloc[2:]
        mean_factor = group_df['Edible conversion factor'].mean(skipna=True)
        mean_factor = round(mean_factor, 1)
        mask = (df['Food_group_code'] == food_group) & (df.index >= 2) & (df['Edible
conversion factor'].isna())
        df.loc[mask, 'Edible conversion factor'] = mean_factor
```

```
    return df

def handle_missing_values(df):
    """Handles missing values in the dataset."""
    df = preprocess_vitamin_a(df)
    df['Vit A-RAE (mcg)'] = df['Vit A-RAE (mcg)'].fillna(0)
    df['Vit A-RE (mcg)'] = df['Vit A-RE (mcg)'].fillna(0)
    df = impute_conversion_factor(df)
    return df

def convert_numeric_columns(df, columns):
    """Convert specified columns to numeric."""
    df[columns] = df[columns].map(clean_and_convert)
    return df

def process_data(file_path):
    """Loads, processes, and saves data into food group CSV files."""
    try:
        df = pd.read_excel(file_path)
        df['Food_group_code'] = df['Code'].apply(get_food_group_code)
        df = handle_missing_values(df)
        df = df.dropna(subset=['Food_group_code'])
        df['Food_group_code'] = df['Food_group_code'].astype(int)
        numeric_columns = ["Protein (g)", "Fat (g)", "Carbohydrate (g)", "Zn (mg)", "Vit A-RAE
(mcg)", "Vit A-RE (mcg)"]
        df = convert_numeric_columns(df, numeric_columns)
        food_groups = {}
        folder_path = 'food_groups'
        os.makedirs(folder_path, exist_ok=True)

        for group in range(1, 16):
            food_groups[group] = df[df['Food_group_code'] ==
group].drop(columns=['Food_group_code'])
            print(f"Food Group {group} Dataframe:")
            print(food_groups[group].head())
            print()
            file_path = os.path.join(folder_path, f'food_group_{group}.csv')
            food_groups[group].to_csv(file_path, index=False)

        print("Data processing and CSV creation completed successfully.")

    except Exception as e:
        print(f"An error occurred: {str(e)}")
if __name__ == "__main__":
    process_data('data3.xlsx')
```

7.8 Appendix D: Front-End Script – React/JavaScript

```javascript
import React, { useState } from 'react';
import './App.css';

function App() {
  const [weight, setWeight] = useState('');
  const [height, setHeight] = useState('');
  const [age, setAge] = useState('');
  const [recommendations, setRecommendations] = useState('');
  const [feedback, setFeedback] = useState('');
  const [error, setError] = useState('');

  const handleSubmit = async () => {
    // Input validation
    if (!weight || !height || !age) {
      setError('Please enter values for weight, height, and age.');
      return;
    }
    if (isNaN(weight) || isNaN(height) || isNaN(age)) {
      setError('Please enter numeric values for weight, height, and age.');
      return;
    }
    const ageInt = parseInt(age, 10);
    if (ageInt < 6 || ageInt > 23) {
      if (ageInt < 6) {
        setError('Exclusive breastfeeding is recommended for children below 6 months of
age.');
      }
      else
        setError('This system only works for kids aged 6-23 months old.');
      return;
    }
    // Clear previous error message
    setError('');
    // POST data to backend
    try {
      const response = await fetch('http://localhost:5000/process-data', {
        method: 'POST',
        headers: {
          'Content-Type': 'application/json'
        },
        body: JSON.stringify({ weight, height, age })
      });
```

```
      if (!response.ok) {
        const errorData = await response.json();
        throw new Error(errorData.error || 'Failed to process data');
      }
      const responseData = await response.json();
      setRecommendations(responseData.recommendations);
      setFeedback(responseData.feedback);
    } catch (error) {
      console.error('Error processing data:', error.message);
      // display error message to the user)
    }
  };
 return (
    <div className="container">
      <h1>Child Weaning Recommendations System</h1>
      <div className="form">
        <div className="input-group">
          <label>Weight (kg):</label>
          <input type="number" value={weight} onChange={(e) => setWeight(e.target.value)} />
        </div>
        <div className="input-group">
          <label>Height (cm):</label>
          <input type="number" value={height} onChange={(e) => setHeight(e.target.value)} />
        </div>
        <div className="input-group">
          <label>Age (months):</label>
          <input type="number" value={age} onChange={(e) => setAge(e.target.value)} />
        </div>
        {error && <div className="error">{error}</div>}
        <button onClick={handleSubmit}>Submit</button>
      </div>
      <div className="output">
        <div className="card">
            <h2>Nutrition Feedback:</h2>
            <div dangerouslySetInnerHTML={{ __html: feedback }} />
          </div>
        <div className="card">
          <h2>Food Recommendations:</h2>
          <p>{recommendations}</p>
        </div>
      </div>
    </div>
  );
}
export default App;
```

7.9 Appendix E: Back-End Script– Python/Flask

```
from flask import Flask, request, jsonify
from flask_cors import CORS
from rules import FeedingExpert

app = Flask(__name__)
CORS(app, origins=["http://localhost:3000"], headers=['Content-Type'])

@app.route('/process-data', methods=['POST'])
def process_data():
    try:
        data = request.json
        weight = int(data.get('weight'))
        height = int(data.get('height'))
        age = int(data.get('age'))

        if age < 6 or age > 23:
            return jsonify({'error': 'This system only works for kids aged 6-23 
months old.'}), 400

        # Create an instance of the FeedingExpert class
        expert = FeedingExpert()

        # Get recommendations from the expert system
        recommendations = expert.get_recommendations(age)

        # Include recommendations from the expert system
        feedback = ""
        feedback += "<br><b>Expert System Recommendations:</b><br>"
        feedback += recommendations

        return jsonify({'recommendations': recommendations, 'feedback': 
feedback})

    except Exception as e:
        return jsonify({'error': str(e)}), 500

if __name__ == '__main__':
    app.run(debug=True)
```