Research Methods Final Report

Ibukun-Oluwa Emmanuella Addy (61162024)

SOAN 325 D: Research Methods

2022/2023 Semester II

06th December 2023

The Role of Artificial Intelligence in the Nutrition Therapy of Africans with Sickle Cell Disease.

Abstract

Sickle Cell Disease is a genetic red-blood cell abnormality that affects 20-30% of the African population. 80% of all sickle cell disease cases are found in Africa, and around 50% of Africans born with sickle cell disease die before age five. [1] This paper aims to highlight the importance of proper nutrition in patients with sickle cell disease and discuss how A.I sub-divisions such as machine learning, computer vision, and expert systems are used to manage nutrition in various diseases. Through in-depth paper studies, interviews with 40 African sufferers of sickle cell disease, interviews with nutritionists, and an experiment setup, this paper aims to demonstrate how artificial intelligence can be used to manage the nutrition of African's with sickle cell disease.

This paper proposes a novel A.I driven nutrition therapy system with three core functionalities, namely: a nutrient level simulator built using python's Sympy, a meal-photo analysis system built using both convolutional neural networks for image recognition and logical programming principles. Finally, a menu planner recommender system using traditional K-means recommender models. The system will be tested by individuals with sickle cell disease, who will assess its ability to recommend accessible and affordable foods, as well as it's alignment with positive health indicators.

Chapter 1: Introduction

Background

Nutrition therapy, also known as medical nutrition therapy (MNT), is an approach to treating medical conditions and their associated symptoms through a tailored diet. It involves the assessment of an individual's nutritional status, the development of a personalized nutrition plan, and the ongoing monitoring and adjustment of the plan as needed. [2]

Since the advent of mobile applications, diet managers, along with many other health and fitness-focused apps like exercise managers, have emerged as some of the most extensively developed and widely used digital health tools. Thanks to rapid progress in Artificial Intelligence, computer software has reached an unprecedented level of capability in assisting individuals with their health and fitness decisions, often surpassing human companions in decision-making processes.

Diet managers can utilize computer vision to help users determine food portions and conduct nutritional assessments. These applications are particularly invaluable for individuals with special Recommended Dietary Allowances (RDAs), such as those living with diabetes, HIV/AIDS, or pregnancy. Diet managers such as SNAQ and GoFoods are far more than applications designed solely to help people achieve aesthetic fitness; they are essential tools governed by safety regulations.

Problem Statement

Since the late 1980s, poor nutrition has been recognized as a challenge for people with sickle cell disease. However, this issue has yet to receive sufficient empirical attention.[3] According to a study published in the Journal of Intelligent Systems with Applications, personalized nutrition advice generated by A.I can lead to a more significant improvement in diet quality compared to generic recommendations. [4] There are two reasons why existing A.I diet managers do not specifically cater to individuals with sickle cell disease. The first reason is that most A.I-driven technologies are trained on data from first-world countries; hence, they fail to recognize and assess most African meals. The second reason is that sickle cell disease is endemic to Africa, with 80% of the cases located here [1], where the basic technological space is still growing. [5]

Purpose/Objective

This research aims to highlight the importance of nutrition in sickle cell disease and demonstrate the potential use of A. I nutrition therapy in managing the disease in Africans.

Hypothesis/Research Questions

The following are some of the questions to be answered in this research paper:

- What is the importance of nutrition in sickle cell disease?
- What Artificial Intelligence Methodologies are currently used by nutrition therapy systems for other diseases?
- Can artificial intelligence methodologies be used to develop a nutrition therapy system for people with sickle cell disease?

Significance of the Research Topic

Suppose an African-inclusive, A.I-driven approach to the nutrition therapy of people with sickle cell disease is proven possible and efficient; software engineers can use the findings to implement a free mobile application for global use. Such an application will give power to individuals to make consistently good health decisions, even when dietician consultation is unavailable, or meal management is time-consuming. This addresses sustainable development goal three(SDG3), concerned with good health and well-being.

Chapter 2: Literature Review and Synthesis

This chapter seeks to show the significance of proper nutrition in individuals with sickle cell disease and emphasize the pivotal role of artificial intelligence (A.I.) in nutrition therapy. The chapter's framework is primarily guided by three models: the Chronic Care Model(CCM), the Technological Task Fit Model(TTF), and the Technological Acceptance Model(TAM). This chapter is structured into five main sections: The Role of Nutrition in Sickle Cell Disease, The Role of A.I. in Nutrition Therapy, Empirical Analysis of A.I. nutrition Therapy Systems Using The TTF model, Challenges and Gaps in A.I. for Nutrition Therapy, and the technological acceptance of A.I. in African healthcare.

I. The Role of Nutrition in Sickle Cell Disease(SCD)

The Chronic Care Model (CCM), developed by Dr. Edward Wagner, is a comprehensive framework to improve the care of patients with chronic diseases. Diverging from traditional acute care models, the CCM advocates for a proactive, patient-centered approach. Widely employed in managing conditions such as diabetes and hypertension, the CCM emphasizes continuity of care and self-management to enhance health outcomes [6]

In a 2014 study that aimed to comprehend the lifestyles of New Yorkers with SCD, a participant in a focus group cited nutrition as a pivotal aspect of their self-management strategy. The individual emphasized preventive health measures to evade hospitalization, spotlighting a commitment to maintaining well-being through proper nutrition, adequate rest, and cultivating a healthy lifestyle to strengthen the immune system [7].

A similar point was made by Hyacinth et al, as their research underscored the imperative for heightened intake of vitamin D and zinc among those with sickle cell anaemia, in conjunction with a unique equilibrium of zinc and copper. [3] Furthermore, the inclusion of magnesium was proposed for alleviating pain during sickle cell anaemia episodes, drawing upon its application in paediatric cases.[8]

A 2023 paper discussed the significance of various other nutrients in managing sickle cell anaemia. The researchers delved into the prevalence of herbal medicine for managing symptoms of SCD, placing emphasis on the proven benefits associated with certain leaves, such as Cajanus cajan and Carica papaya, in resisting haemolysis and diminishing sickled red blood cells. [9] Furthermore, they presented an augmented nutritional requirements table for individuals with sickle cell anaemia, encompassing protein, carbohydrates, omega-3 fatty acids, vitamins B6, vitamin B12, vitmanin A, vitamin C, vitamin D, vitamin E, folate, magnesium, zinc, and selenium. [9]

Researchers affiliated with the Philadelphia Biomedical Research Institute and Ibadan University conducted an experiment involving the collection of blood samples from sickle cell anaemia patients in the United States and Nigeria. The study identified a subset of red blood cells termed "dense cells" with abnormal characteristics contributing to painful vasoocclusion. Laboratory experiments revealed that specific nutritional antioxidant supplements, hydroxyl radical scavengers, and iron-binding agents could inhibit the formation of dense cells. The recommended daily nutritional intake encompassed 6 grams of aged garlic extract, 4–6 grams of vitamin C, and 800 to 1200 IU of vitamin E. [10]

Most interestingly, it has been discovered that biological sex can play a role in nutrition for sickle cell anameia. A comprehensive evaluation conducted in Tanzania underscored that male patient with sickle cell anaemia generally experienced more adverse nutritional conditions than their female counterparts. [11]

II. The Role of Artificial Intelligence(A.I) in Nutrition Therapy

This section categorizes Nutrition Therapy Systems based on the predominant A.I technique employed in development. The identified methodologies include machine learning, computer vision, and expert systems. Machine Learning involves the creation of algorithms and models that empower computers to learn and enhance their performance through experience. A notable application of machine learning is in recommendation systems. [12] On the other hand, Computer Vision seeks to enable computers to interpret and comprehend visual information. This includes tasks such as image recognition and object detection. [13] Finally, Expert Systems are specialized computer systems designed to replicate the decision-making capabilities of human experts in specific domains. They utilize knowledge bases and inference engines to emulate human expertise. [14]

Machine Learning

- **Non-human Nutrition**

In 2006, Robbins and Saxtion conducted an experiment with pigs and fish to figure out their nutritional needs. They used a method called broken-line regression, to estimate the nutritional needs of the animals. The researchers compared different broken-line regression models and found that a quadratic broken-line model worked best for their data because it considers the non-linear way animals respond to nutrients. They also used a statistical analysis procedure called Non-Linear Mixed models, which helps include additional factors like gender and initial weight. The study highlighted the importance of using sophisticated models to understand how animals respond to nutrients and paved the way for further involvement of machine learning in food and nutrition. [15]

- **Multi-Disease Nutrition**

In 2023, Ahmad and Khan undertook the development of a food recommendation system that addressed diverse health conditions concurrently, encompassing iron deficiency, kidney diseases, diabetes, and hypertension. The authors used a nutrition-based food dataset, which contained information about the nutritional content of various foods, such as calories, macronutrients, micronutrients, etc. They also collected input data from the user to generate a health profile containing details about an individual's health, including age, gender, and existing health conditions. [16]

A specialized algorithm was then employed to calculate the specific nutritional needs of each individual based on their health profile. The k-means Clustering algorithm was utilized to cluster foods based on nutritional similarities. By categorizing foods with similar nutritional profiles, the system could recommend food alternatives within the same cluster, enhancing the personalization of dietary suggestions. The research affirms the system's proficiency, accuracy, and ability to provide relevant food recommendations based on user health conditions, as demonstrated by excellent precision, recall, and F-1 Score metrics. [16]

A similar research developed a Dietary Recommendation System using a Gated Recurrent Unit (GRU), data from 50 patients and over a thousand foods. The study applied the cosine similarity algorithm for data matching, followed by K-clique clustering to train a model for personalized diet suggestions.[17]

In another research endeavor, 16 decision trees were employed to provide personalized dietary guidance based on data derived from a web-based Food Frequency Questionnaire (FFQ). The questions were intended to find out what a user eats regularly. These decision trees, adhering to the Institute of Medicine's (IOM) gradation system, autonomously linked computed nutrient intake values to feedback from a library containing 92 template messages. The decision trees covered a spectrum of nutrients, classifying a user's nutrient intake levels as "low," "recommended," or "high.". The feedback messages not only conveyed information about nutrient status but also provided practical suggestions for enhancing nutrient intake. [18]

Computer Vision

- **General Nutrition**

In a Swiss study, volunteers were enlisted to record brief videos of their daily food and beverage intake using the goFOODTM Lite application. The application works with single images of real food or barcodes of processed foods. The accuracy of the goFOODTM system's estimation of the participants' calorie and macronutrient consumption was then evaluated. [19] The results of this would be discussed in the empirical analysis section of this paper, while the computer vision frameworks and computing procedures used for building goFOODSTM is explained in this section. goFoodsTM utilized a dataset comprising 57,000 images from MyFoodRepo dataset version 2.1 was compiled for the segmentation task. [15] The segmentation task used a Convolutional Neural Network (CNN) based on Mask RCNN pre-trained on the COCO dataset, with ResNet-50 as the backbone. For the image classification task, approximately 200,000 images were obtained and categorized. Each segmented item was processed by a food recognition network using RegNetY-16GF. Mix-up interpolation was used in the training process for the recognition. [19]

The food volume estimation module employed depth maps to convert 2-D representations of food items into a 3-D space. Two approaches were used: the Neural-Based Approach and the Geometry-Based Approach. [19] In the Neural-Based Approach, single images captured at a 90° angle were used for depth estimation, leveraging the Zoe model, which incorporates multiple depth modules in an encoder-decoder architecture. [19] The Geometry-Based Approach eliminates the need for a plate in the food image, by detecting key points from reference cards and segmentation masks, rectifying stereo image pairs for depth information, and converting the resulting disparity map into a depth map for volume estimation. [19]

Similar to goFoodsTM, another group of researchers developed an innovative neural network architecture named DelicacyNet, comprising four main modules: an environment feature extraction module, an encoder, a decoder, and a semantic output module. [20] The system analysed and identified the primary nutrients in the food's raw materials when provided with food images. The process involved extracting environmental features from the images, processing them through the encoder, and presenting the results as a text table using the decoder. Their model exhibited high accuracy in predicting food components, making it applicable in practical scenarios. [20]

Expert Systems

- **Cancer Nutrition**

The Personalized Diet Recommendation System by Hussain et al, aims to assist cancer patients in planning their daily diets. It employs Case-based Reasoning, Rule-based Reasoning, and Genetic Algorithm to create customized diet menus based on individual health information. Users input data such as cancer type, treatment stage, activity level, food preferences, allergies, ethnicity, and side effects to build their profiles. [21] The system consists of four modules: user management (for login and authentication), diet planning (utilizing Case-based and Rule-based Reasoning), menu construction (using a food database and Genetic Algorithm), and menu adaptation (suggesting substitutes based on Rule-based Reasoning). The outcome is a system that recommends a personalized daily dietary allowance for energy, carbohydrate, protein, calcium, thiamin, niacin, riboflavin, vitamin A, vitamin C, vitamin D, and vitamin E. Based on these recommendations, the system suggests breakfast, lunch, and dinner menus tailored to the user's specific needs. [21]

- **Diabetes Nutrition**

In 2018, Alian and Pandy addressed the rising diabetes epidemic in American Indian communities by proposing a mobile application for proactive diabetes self-care. The application utilizes users' ontological profiles, incorporating socio-economic, cultural, and geographical factors, to deliver personalized eating habit recommendations. The diabetes management system relies on logical programming and a knowledge base built on general diabetes information, food and nutrition facts, and American Indian healthcare guidelines from the American Diabetes Association. This knowledge is translated into rules using a "premise→conclusion" logic form. [22] Expressed in the Semantic Web Rule Language (SWRL), these rules cover diverse aspects of diabetes management and are processed by a reasoning engine using forward chaining. [22]

- **General Nutrition**

Existing diet recommendation systems commonly utilize Case-Based Reasoning (CBR), Rule-Based Reasoning (RBR), or a hybrid approach combining both, such as the Case-Base Menu Planner (CAMP), CAMP Enhanced by Rules (CAMPER), and Pattern Regulator for the Intelligent Selection of Menus (PRISM). CAMP's case base comprises 84 daily menus that adhere to the Reference Daily Intake (RDI) and Dietary Guidelines for Americans. The system operates by retrieving and adapting menus from its knowledge base. On the other hand, PRISM is a rule-based menu planner that employs a multilayered hierarchical structure to generate menus based on nutrient constraints. [21]

III. Empirical Studies of AI-based Nutrition Therapy Systems using the Task Technology Fit Model

The Task-Technology Fit (TTF) model is a conceptual framework designed to evaluate how well a particular technology aligns with the requirements and characteristics of a given task or set of tasks within an organization. [23] In the goFoodsTM research, it was found that the chosen method, using just one image of food taken by the user, had an average error of 27.41% in estimating calories per person. Additionally, it had errors of 31.27% for carbohydrates (CHO), 39.17% for protein, and 43.24% for fat compared to human dieticians estimations. [19] Another similar study tested a new U.S.A domiciled computer vision app called SNAQ. SNAQ takes pictures of a user's food to determine what an adult human should eat and how much. The researchers wanted to see if SNAQ can accurately measure how much energy a woman has consumed, compared to a human traditional method called 24-hour dietary recall (24HR) and a reference method called doubly labeled water (DLW). They found that SNAQ did better than 24HR in estimating how much energy a woman gets from food. SNAQ and 24HR had similar results in estimating energy and the types of nutrients obtained from food. Through statistical comparison, the researchers concluded that SNAQ seems to be better than 24HR at estimating energy intake, but more research is needed to see how well it works with a very large number of users. [24]

In the Food4Me Proof-of-Principle study by Walsh et al, 1607 participants across Europe where offered personalized nutrition advice from both human dieticians and the Food4Me automated system. [18] All participant's nutrient goals were grouped into three broad categories: nutrient goals one to three. In evaluating nutrient-related goals, the results showed generally high agreement between human dieticians and the automated system (92% for goal 1, 87% for goal 2, and 87% for feedback advice). Still, some disagreements were noted, especially in goal three. [18]

II. Challenges and Gaps with A.I For Nutrition Therapy

Gaps

Most AI research on Nutrition Therapy is led by non-African entities, resulting in a significant absence of African-origin data in the training of intelligent systems. This observation is particularly underscored by the absence of pertinent literature emanating from African sources.

Another shortcoming is in the context of specialized digital nutrition therapy systems tailored for individuals with Sickle Cell Anemia. While abundant literature is available on digital nutrition therapy for obesity, diabetes, and general well-being, a conspicuous gap exists concerning comprehensive studies on SCD, particularly within the African context.

Technical Challenges

Efficient nutrition therapy poses a technical challenge, necessitating a deep understanding of machine learning models. Group recommender models, employing Naïve Bayes, SVM, and RM algorithms, face criticism for their narrow focus on single-disease dietary recommendations. Some advocate for collaborative-based algorithms, asserting greater efficacy in providing optimal food suggestions. [16]

Suggestions

Lee et al, propose enhancing a diet recommendation system by integrating vital sensors for real-time user data collection, including pulse rate, temperature, respiration rate, and blood pressure. [25] Also, research in Nutrigenomics aim to incorporate human genome data, to enhance the accuracy of dietary recommendations. [26]

Constraints

Creating an AI-driven Nutrition Therapy system is sometimes costly due to gathering extensive data on food images, ingredients, quantities, and personal medical information. Legal considerations, including food and drug regulatory approvals, add even more complexity. The paper "A Conceptual Framework for Adaptive Personalized Nutrition Advice Systems (APNASs)" highlights concerns about personalized nutrition favoring financially advantaged groups, partly due to fees in end-user diet management apps. [27]

V. The Technological Acceptance of A.I in African HealthCare

The Technology Acceptance Model (TAM), introduced by Fred Davis in the late 1980's posits that users' acceptance of technology is influenced by two key factors: Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). [28] In 2013, the WHO Regional Committee for Africa, adopted Resolution AFR/RC63/R5. [5] This resolution urged Member States to embrace digital health initiatives, emphasizing leadership, coordination, and investments in information and communication technologies (ICTs) for healthcare.

The current situation in Africa reflects significant ICT growth, Mobile telephony penetration increased from 32.2% in 2008 to 83.2% in 2020, Mobile broadband penetration rose from 1.7% in 2008 to 33.1% in 2020, Individual internet users increased from 4% in 2008 to 30% in 2020. [5]

Nigerian start-up Ubenwa uses signal processing and machine learning to enhance birth asphyxia diagnosis in low-resource settings. In Zambia, AI effectively diagnoses diabetic retinopathy, outperforming human assessments. The Delft Institute's CAD4TB software demonstrates promising results in detecting pulmonary tuberculosis from chest radiographs in Tanzania and Zambia, comparable to human experts. [29]

VI. Conclusion

This chapter explored AI-driven nutrition therapy systems, which assessed users' meals through image analysis or recommended meals based on health profiles. The examination revealed that accessible AI methodologies offered significant opportunities for the nutrition therapy of people with special health requirements. Positive empirical study results on the efficiency of AI in nutrition therapy suggest that the TAM requirement of Perceived Usefulness(PU) of a nutrition therapy system has been demonstrated by this paper.

In line with the WHO AFRO agenda for digital health, the technical, political, and social landscape can support the development of a non-invasive, user-friendly digital tool for Africans with SCD. Therefore, A.I is a feasible approach to delivering nutrition therapy to Africans with SCD.

Chapter 3

A. Methodology

The purpose of this chapter is to outline the data collection procedures, data analysis tools, experimental setup, and technological frameworks used in a proposed experiment to answer the research question: Can artificial intelligence be used to improve the nutrition therapy of Africans with sickle cell disease? The research is a mixed-method research involving qualitative and quantitative research design.

B. Experiment setup and Computational Model

Data Collection

To perform a situational analysis and needs assessment**,** the research begins with audio-recorded interviews of 40 sickle cell disease patients, organized into four focus groups, representing East Africa, West Africa, South Africa, and Central Africa. For each focus group, the selection of the 10 participants will be done using stratified random sampling where income bracket and biological sex are the strata. These focus group interviews will use a multi-question questionnaire in a tele-conferencing setup to explore the participants' experiences with nutrition and get insights into their daily schedules, meal expenditures, and available foods.

Healthcare professionals contribute valuable information on the recommended meals and nutrients for individuals with sickle cell disease; hence, the study also extends its scope by incorporating audio interviews with the Head Nurse of Natemba Health Center, five nutritionists selected by African region strata, and two randomly selected medical doctors. The gathered audio data is transcribed using Google’s speech-to-text platform, and coded using Computer Assisted Text Markup and Analysis(CATMA) Software.

The interview process will allow for streamlining the technical data collection process, where high-quality pre-labeled and cleaned images of over 100,000 African meals and 200,000 international meals similar to the meals discussed in the focus group sessions will be collected. The images will be collected from data repositories such as MyFoodRepo, RoboFlow, Kaggle, CamerFood10(the first food images dataset specifically designed for sub-Saharan African food segmentation), and KenyanFood13.

Tools and Frameworks

Mask R-CNN with Res-Net50 as the backbone or MidDeepLabv3 with ResNet50 as a backbone will be used for image Segmentation tasks. To distinguish between food and non-food content in images, the system will adopt the ResNeXt101 model, pre-trained on the Common Objects in Context (COCO) dataset. YOLOv5 engine or TensorFlow's CNN with ResNet-50 or RegNetY-16GF as the backbone will be used for training an image recognition model to recognize various meals. Food Volume Estimation will be done using Python's Zoe-Depth Estimation Model. SQLite and PROLOG files will be used for storage, while various Python libraries will be used for biological simulations.

Computational Model(System Design & System Architecture)

The computational model of the nutrition therapy system is an offline application divided into two main sub-systems: a knowledge-based system and a decision-making system.

<u>Knowledge Base Sub-module 1 (Recommended Daily Allowance Profile)</u>

Users input information about themselves, such as age, sex, occupation, exercise information, and health conditions. This user information will be fitted into an RDA equation for sickle cell disease, in order to generate the 24-hour Recommended Daily Allowance of Nutrients and calories for each user.

Knowledge Base Sub-module 2 (Nutrient Level Tracker)

The Nutrient Level Tracker is visualized by a dashboard that shows a user's nutrient levels in real time. Zinc, Copper, and Magnesium Levels are critically calculated and monitored.

For the nutrient level tracker, a dynamic biochemical processes simulation will be built using established mathematical models for nutrient consumption, e.g., differential equations such as Miller's Mathematical Model of Zinc Absorption in Humans As a Function of Dietary Zinc and Phytate. [30] The process will be visualized using the Seaborn Python library and simulated using Simpy, PyDS tool, SciPy, or NumPy for Ordinary Differential Equation Solving.

Knowledge-Base Sub-Module 3 (Digital Stomach)

Using photographs or manually inputted text, the digital stomach will serve as a record of meals a user has eaten and the time it was eaten. An SQLite database will be used to represent the digital stomach.

Knowledge-Base Sub-Module 4 (Foods-Nutrients Database)

A database of foods and their corresponding nutrients and calories. The Food and Nutrients database will be represented by SQLite files.

Knowledge-Base Sub-Module 5 (Sickle Cell Nutrition Facts)

A database containing critical facts about sickle cell disease was gathered during interviews with healthcare professionals. The database is represented by PROLOG files. PROLOG is a high-level programming language built on predicate calculus. An example of a predicate in PROLOG: *'is_mildly_unsafe(monosaccharide)'* meaning monosaccharide is mildly unsafe.

Decision-Making Sub-module 1 (Nutritional Assessment of Meals Using Images).

When a user takes a picture of a meal, the food is automatically analyzed for nutrients using an image classification model in tandem with the sickle-cell nutrition knowledge base and food-nutrients knowledge base. A report of the meal's nutritional content is shown, and the user is advised either to eat or not to eat the food based on their digital stomach contents and nutrient levels. The module also looks out for unique possible allergies or interactions. If a user clicks eat, the meal is added to their digital stomach.

The meal analyzer will be constructed using SWI-PROLOG, a LOGIC programming software. The data in the SQLite and predicates in PROLOG files are combined to form various premises, which result in a yes or no conclusion about consuming a meal. These premises to conclusions are called "rules".

% Rule: If X is a carbohydrate and X is fried, X is unhealthy.

% Facts: is_carboydrate (Potato Chips), is-fried (Potato chips).

% Query: -? -healthy (Potato Chips)

% Query Result: false

Decision-Making Sub-Module 2(Meal Recommender and Reminder Module)

This module is in charge of recommending meals to the user when it detects that certain nutrient levels or caloric levels might be running low. It reminds a user to recharge with certain foods. A user can also press the recommend button without using the automatic reminder feature, and the same process will be followed.

Decision-Making Sub-Module 3(Menu Planner)

Each user has a daily menu of Breakfast, Lunch, Dinner, and Snacks constructed for them, which is changed daily based on information in the dynamic knowledge base. K-means clustering will be used for the menu planner and meal recommendation system.

C. Expected Results

The module for nutritional assessment of meals using images is expected to achieve high F1, Accuracy, and Recall scores. The nutrient level simulation module is expected to achieve positive correlation values when the nutrient simulation module is regressed with real-world experiment results. The meal recommender module is expected to consistently recommend available and preferred foods to the user. Finally, the overall system is expected to give rise to positive health indicators for the user.

D. Rest of Work to Be Accomplished

Assembling the system into a widely accessible mobile application that follows the software development life cycle is a possible next step.

E. Validation

System Validation

The food image data will be split into training and testing, and after the model is trained, the pre-labeled testing data will be fed to the image classification model. Accuracy, Precison, Recall and F-1 scores will be calculated for the test data. The F1 score is the harmonic mean of precision and recall. Accuracy is the ratio of correctly predicted instances to the total instances. Precision is the ratio of true positives to the total predicted positives, and recall is the ratio of true positives to the total actual positive.

Measuring the accuracy of the nutrient tracker module involves using standard biochemical simulation performance metrics, such as k-fold cross-validation and comparison with real-world experiment results. Statistical tools, such as regression analysis, can quantify the agreement between the simulation and real-world experiment results.

User Validation

The Technology Acceptance Model (TAM) will be employed to assess the Perceived Ease of Use (POU) and Perceived Usefulness (PU) of the system. The evaluation will involve a questionnaire and the 40 members of the interview focus group. Users will specify any noticeable improvements or declines in their health during the system's use. Feedback regarding system satisfaction will be gathered through a predefined questionnaire comprising 20 questions. The questionnaire will aim to capture users' experiences on various aspects, including but not limited to bodily fatigue, occurrences of painful sickle cell crises, energy levels, and the feasibility of the recommended meals. Finally, the relationship between using the system and changes in users' health will be determined using a chi-square test.

F. Risk Management

Ethical concerns could arise in the recorded focus group sessions, where participant's information must be kept private. The best way to maintain data safety and confidentiality is to use pseudonyms for the focus group participants and voice distortion when recording. There is a general concern with user bio-data being collected in the system. To maintain anonymity, information such as names, email addresses, and phone numbers will not be collected by the system.

A well-detailed data consent agreement will be signed by all testers of the system and stakeholders interviewed in the data collection stage. All data and computational models will also be backed up in the cloud to avoid data loss from corruption or hardware failure.

Potential Limitations to this system include the lack of consideration for drug interactions because medications are not recorded by the system, and medication is known to interact with food. A disclaimer will be made to all users about this.

G. Schedule and Timeline

The development of the system is estimated to take 100 working hours. After system completion, the 40 aforementioned users will engage with the system over two weeks.

H. Summary of Proposal

In summary, an experiment to test the efficiency of an A.I driven nutrition therapy system specific to Africans with sickle cell disease will be conducted, consisting of 100 hours of experiment setup and two weeks of user testing.

References

[1]World Health Organization Regional Office for Africa. (n.d.). Sickle-cell disease. Retrieved from https://www.afro.who.int/health-topics/sickle-cell-disease#:~:text=Sickle%2Dcell%20disease%20is%20characterized,blood%20vessels%2C%20impairing%20blood%20flow

[2]Hernández, A. (n.d.). "Medical Nutrition Therapy: What Is It, Uses, Examples, and More." Alyssa Haag, Kelsey LaFayette (Eds.), Jessica Reynolds (Illus.), Stacy Johnson (Copyed.). *Osmosis*. Retrieved December 5, 2023, from https://www.osmosis.org/answers/medical-nutrition-therapy#:~:text=Medical%20nutrition%20therapy%20is%20a%20treatment%20provided%20by%20nutritional%20professionals,in%20one's%20diet%20or%20lifestyle

[3] Hyacinth, H.I., Gee, B.E., and Hibbert, J.M. 2010. The Role of Nutrition in Sickle Cell Disease. *Nutrition and Metabolic Insights*, 3(57-67). https://doi.org/10.4137/NMI.S5048

[4] Ülker, İ., & Ayyıldız, F. (2021). Artificial Intelligence Applications in Nutrition and Dietetics. *Journal of Intelligent Systems with Applications*, 125-127. https://doi.org/10.54856/jiswa.202112175

[5] World Health Organization. (2021). Framework for Implementing the Global Strategy on Digital Health in the WHO African Region. AFR/RC71/10, Regional Committee for Africa, Seventy-first session, Virtual session, 24–26 August 2021.

[6]Wagner, E. H., Austin, B. T., and Von Korff, M. 1996. Improving outcomes in chronic illness. *Managed Care Quarterly* 4, 2 (1996): 12-25.

[7]Williams-Gray B., Senreich E (2015) Challenges and Resilience in the Lives of Adults with Sickle Cell Disease, Social Work in Public Health, 30:1, 88-105, DOI: 10.1080/19371918.2014.938396

[8] Brousseau DC, Scott JP, Hillery CA, et al. The effect of magnesium on length of stay for pediatric sickle cell pain crisis. Acad Emerg Med. 2004;11(9):968–72.

[9] Umeakunne K, Hibbert JM. 2019. Nutrition in sickle cell disease: recent insights. Nutrition and Dietary Supplements, 11, 9-17. DOI: https://doi.org/10.2147/NDS.S168257

[10] S. Tsuyoshi Ohnishi, Tomoko Ohnishi, and Gabriel B. Ogunmola. Sickle Cell Anaemia. 2000: A Potential Nutritional Approach for a Molecular Disease. Nutrition; 16, 330-338. DOI:10.1016/S0899-9007(00)00257-4

[11] Cox S.E, Makani J, Fulford A.J, Komba AN, Soka D, Williams TN, Newton CR, Marsh K, and Prentice AM. 2011. Nutritional status, hospitalization, and mortality among patients with sickle cell anemia in Tanzania. Haematologica, 96(7), 948-953. DOI: https://doi.org/10.3324/haematol.2010.028167

[12] Breiman, L. 2001. Statistical Modeling: The Two Cultures. Statistical Science 16, 3 (2001), 199–231.

[13] Lowe, D. G. 2004. Distinctive Image Features from Scale-Invariant Keypoints. International Journal of Computer Vision 60, 2 (2004), 91–110.

[14] Feigenbaum, E. A., & McCorduck, P. 1983. Expert Systems in the Micro-Electronic Age. Scientific American, 249(3), 180–199.

[15]K. R. Robbins, A. M. Saxton, and L. L. Southern. 2006. Estimation of nutrient requirements using broken-line regression analysis. *J. Anim. Sci.* 84, E. Suppl. (2006), E155–E165.

[16] M. Ahmad, A. U. Khan, and M. Sajid. 2023. A Diet Recommendation System for Persons with Special Dietary Requirements. Journal of Computing & Biomedical Informatics 05, 01 (2023), Article 180-0501. ISSN: 2710-1606. https://doi.org/10.56979/501/2023

[17] S. Manoharan and S. Ammayappan. 2022. Patient Diet Recommendation System Using K Clique and Deep Learning Classifiers. Journal of Artificial Intelligence and Capsule Networks, 02(02), 121-130. ISSN: 2582-2012 (online). DOI: https://doi.org/10.36548/jaicn.2020.2.005

[18] H. Forster, M. Walsh, C. O'Donovan, C. Woolhead, C. McGirr, E. Daly, R. O'Riordan, C. Celis-Morales, R. Fallaize, A. Macready, C. Marsaux, S. Navas-Carretero, R. San-Cristobal, S. Kolossa, K. Hartwig, C. Mavrogianni, L. Tsirigoti, C. Lambrinou, M. Godlewska, A. Surwiłło, I. Gjelstad, C. Drevon, Y. Manios, I.

Traczyk, J. Martinez, W. Saris, H. Daniel, J. Lovegrove, J. Mathers, M. Gibney, E. Gibney, and L. Brennan. 2016. "A Dietary Feedback System for the Delivery of Consistent Personalized Dietary Advice in the Web-Based Multicenter Food4Me Study." Journal of Medical Internet Research 18, 6 (2016), e150. https://www.jmir.org/2016/6/e150. DOI: 10.2196/jmir.5620.

[19] Papathanail, I., Rahman, L. A., Brigato, L., Bez, N. S., Vasiloglou, M. F., van der Horst, K., & Mougiakakou, S. 2023. The Nutritional Content of Meal Images in Free-Living Conditions—Automatic Assessment with goFOODTM. Nutrients, 15(17), 3835. [DOI: 10.3390/nu15173835](https://doi.org/10.3390/nu15173835)

[20] Li, R., Ji, P., and Kong, Q.(2023) DelicacyNet for nutritional evaluation of recipes. Frontiers in Nutrition, Sec. Nutrition Methodology, Volume 10, 22 September 2023, Article Number 1255499. DOI: https://doi.org/10.3389/fnut.2023.1247631

[21] Husain, W., Wei, L. J., Cheng, S. L., and Zakaria, N (2011) Application of Data Mining Techniques in a Personalized Diet Recommendation System for Cancer Patients," In Proceedings of the 2011 IEEE Colloquium on Humanities, Science and Engineering Research (CHUSER 2011), Dec 5-6, 2011, Penang, Malaysia.

[22]Alian, S., Li, J., and Pandey, V. (2018) A Personalized Recommendation System to Support Diabetes Self-Management for American Indians," IEEE Access, vol. 6, pp. 73300-73309. DOI: 10.1109/ACCESS.2018.2882138.

[23] Chin, W. W. (1998). The Development of the Task-Technology Fit Model for Assessing User Satisfaction with Information System. ACM Management Information Systems Quarterly, 22(2), 213-236. https://doi.org/[DOI]

[24] Serra, M., Alceste, D., Hauser, F., Hulshof, P. J. M., Meijer, H. A. J., Thalheimer, A., Steinert, R. E., Gerber, P. A., Spector, A. C., Gero, D., Bueter, M. (2023). Assessing Daily Energy Intake in Adult Women: validity of a food recognition mobile application compared to doubly labeled water. Frontiers in Nutrition, Sec. Nutrition Methodology, Volume 10, 22 September 2023, Article Number 1255499. DOI: https://doi.org/10.3389/fnut.2023.1255499.

[25] Kim, J.-H., Lee, J.-H., Park, J.-S., Lee, Y.-H., & Rim, K.-W. (2009). Design of Diet Recommendation System for Healthcare Service Based on User Information. In Proceedings of the 2009 Fourth International Conference on Computer Sciences and Convergence Information Technology. Incheon, Korea.

[26]Holzapfel, C., Dawczynski, C., Henze, A., & Simon, M.C. (2021). Personalized dietary recommendations for weight loss: A scientific perspective from various angles. Ernahrungs Umschau, 68(2), 26–35. DOI: 10.4455/eu.2021.008.

[27] Renner, B., Buyken, A. E., Gedrich, K., Lorkowski, S., Watzl, B., Wirsam, J. 2023. Perspective: A Conceptual Framework for Adaptive Personalized Nutrition Advice Systems (APNASs). Advances in Nutrition, 14(5), 983-994. ISSN 2161-8313. https://doi.org/10.1016/j.advnut.2023.06.009

[28]Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340.

[29] Owoyemi A, Owoyemi J, Osiyemi A and Boyd A (2020) Artificial Intelligence for Healthcare in Africa. Front. Digit. Health 2:6. doi: 10.3389/fdgth.2020.00006.

[30] Miller LV, Krebs NF, Hambidge KM. A mathematical model of zinc absorption in humans as a function of dietary zinc and phytate. *J Nutr*. 2007;137(1):135-141. doi:10.1093/jn/137.1.135