A Study of Artificial Intelligence Approaches in Nutrition Therapy for Ghanaians with Sickle Cell Disease:

Traditional Expert Systems

VS.

LLM-augmented KG Question Answering

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ABSTRACT

Modern Digital Diet Managers offer a range of artificial intelligence-driven services to help people with special dietary needs or diseases make smarter decisions regarding their food intake and overall nutrition. Computer Vision and Recommendation systems are among the popular artificial intelligence methodologies used in managing the diet of Diabetics, Hypertensives, and Cancer patients, however, this technology is yet to be adopted in the nutrition therapy of Sickle Cell Disease(SCD), especially in Africa, where 80% of SCD cases are located, and 1 in 4 people suffer from the disease. [1]

This study conducted an experiment aimed at comparing and contrasting sickle cell dietary advice reports generated by two distinct systems: an AI assistant constructed using SQLite databases with rule-based conditional programming and a large language model enhanced with a knowledge graph for generating prompt responses.

The research also used a computer vision module to recognize and determine the portion of Ghanaian meals before passing the result to the decision-making system and the Large Language Model.

Python's spaCy library was utilized to determine the similarity between the reports generated by the Traditional Expert System and those generated by the Knowledge-Graph Augmented Large Language Model.

YOLOV8 with a CNN-ResNet-50 backbone and Python's Zoe depth estimation model were used for image classification and depth estimation, respectively.

CCS CONCEPTS
•Expert Systems •Artifical Intelligence •Large Language Models.

KEYWORDS:
Sickle Cell Disease, Computer-Vision, YOLOV8, CNN, LLM, ResNet, Nutrition.

INTRODUCTION

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 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. [2] In 2019, Hibbert and Umeakunne's paper discussed the significance of various other nutrients in managing sickle cell anemia. 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. 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, vitamin A, vitamin C, vitamin D, vitamin E, folate, magnesium, zinc, and selenium. [3]

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. [4]

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 [5].

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 humans in decision-making.

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. [6]

Digital 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.

BACKGROUND

Theoretical Framework

A knowledge graph (KG) is a structured representation of knowledge, typically in entities, their attributes, and the relationships between them. It can model real-world information and facilitate understanding and reasoning about data. [16]

LLM-augmented KG Question Answering (KGQA) aims to find answers to natural language questions based on structured facts stored in knowledge graphs. LLMs can serve as:

- Entity/relation Extractors: Identifying entities and relationships mentioned in natural language questions and retrieving related facts in KGs. LLMs can effectively perform this task due to their proficiency in language comprehension.
- Answer Reasoners: Reasoning over retrieved facts to generate answers directly. LLMs can be used for answer reasoning to generate answers based on the retrieved facts.

Historical Context

In 2019, Hibbert and Umeakunne published a recommended daily allowance table of nutrients for people with SCD. [3] However, there is still a gap, as there is no A.I system to help track those specific nutrient intakes or to examine meals for possible interaction with sickle cell disease medication.

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 where the basic technological space is still growing. [7]

In a pedagogical paper on computer science for food and nutrition, Robbins and Saxton experimented with pigs and fish to determine 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.

The authors 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 human nutrition. [8]

With the above findings as the proof-of-concept, this research seeks to answer the following research Questions:

- Do Knowledge Graph Augmented Large Language models Perform Better than traditional rule-based expert systems in the Nutrition Therapy of Ghanaians with Sickle Cell Disease?
- Can a Rule-Based Expert system generate similar feedback reports to a Knowledge Graph Augmented Large Language Model in the Nutrition Therapy of Ghanaians with sickle cell disease?

RELATED WORKS

I. Recommendation Sytems

In 2023, Ahmad and Khan developed 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. [9] A specialized algorithm was then employed to calculate the specific nutritional needs of each individual based on their health profile.

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. [10] 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. [10]

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. [11]

II. Expert Systems

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 algorithms 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, carbohydrates, 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. []

III. Computer Vision Systems

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. [12].

goFoodsTM utilized a dataset comprising 57,000 images from MyFoodRepo dataset version 2.1. [12] 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 recognition training process. [12]

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. [12] 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. [12]

The research found that by using just one image of food taken by the user, there was 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.

Similar to goFoodsTM, another group of researchers developed an innovative neural network architecture named Delicacy Net, comprising four main modules: an environment feature extraction module, an encoder, a decoder, and a semantic output module. [13]

The system analyzed and identified the food's primary nutrients when provided with 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. [13]

In the Food4Me Proof-of-Principle study by Walsh et al., 1607 participants across Europe were offered personalized nutrition advice from human dieticians and the Food4Me automated system. [14] 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.

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 traditional human 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 assessing 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. Still, more research is needed to see how well it works with a large number of users. [15]

IV. Large Language Models

A Copilot framework presents an innovative approach to utilizing LLMs in specialized tasks, eliminating the necessity for model fine-tuning. [17]

In 2024, Ren et al. compared various Large Language Models against one another to see which was most efficient in serving as a general health consultant. The Healthcare Copilot, designed for medical consultation, comprises Dialogue, Memory, and Processing components. Dialogue facilitates patient interactions, Memory stores conversation data, and Processing generates reports. [17]

The evaluation of the proposed Healthcare Copilot involved the use of four popular Language Model (LLM) backbones: GPT-4 1106-preview, GPT-3.5-turbo, LLaMA2-70b-chat, and ChatGLM3-6B. [17]

The experiment primarily utilizes ChatGPT as virtual patients in simulating medical consultations. Real cases from the MedDialog dataset are used as references to ensure authenticity and relevance in simulated medical scenarios. Four key metrics are used to evaluate the Healthcare Copilot comprehensively:

- Inquiry capability: assesses the ability to ask accurate and relevant questions.
- Conversational fluency: measures the user experience within the dialogue context.
- Response accuracy: showcases the preciseness of model responses.
- Response safety: describes the model's compliance with safety and ethical standards during its responses.

The integration of Healthcare Copilot yielded noticeable enhancements in response accuracy across all models. Additional information gathered by the Inquiry module and rectifying inaccuracies through the Safety module contributed significantly to this improvement. GPT-4, with its advanced capabilities, outperformed other general LLMs, and Healthcare Copilot consistently enhanced its performance, demonstrating remarkable generalization abilities. [17]

METHODOLOGY

Data Collection

5000 images of various African meals and Ghanaian meals were downloaded from RoboFlow and annotated using CVAT, which stands for Computer Vision Annotation Tool, which is a free open-source software for image and video annotation.

Nutrient intake allowances for persons with SCD for protein, carbohydrates, omega-3 fatty acids, iron, vitamins B6, vitamin B12, vitamin A, vitamin C, vitamin D, vitamin E, folate, magnesium, zinc, and selenium. (Sub-divided by age and gender) was obtained from the only publicly available recommended daily intake table for sickle cell disease, published by Hibbert and Umeakunne in 2019.

Sickle Cell Disease medication names, compounds, and their possible interactions with certain foods were obtained from the online databases of the American Center for Disease Control, papers from the American National Library of Medicine, and information on approved treatment medications for sickle cell disease from the sickle cell anemia news platform. Chemical compounds present in various foods were obtained from FooDB. FooDB is an openly available internet-based repository of foods and the compounds and nutrients present in them. The Database contains information about approximately 900,000 foods stored in JSON format.

Nutrients found in Ghanaian foods per serving of 100 grams were obtained from Kaggle, and My Fitness Pal Database, as well as numerous food blog websites, listed in the appendix of this report.

User information such as stomach content, weight, height, age, and sex were provided by user input once the program started.

Experiment Setup

Using YOLO V8, a CNN-ResNet50 image recognition model was built and trained on 5000 images of Ghanaian and African foods. The model was trained with epoch=100 to perform instance segmentation and image classification. Instance Segmentation is a computer vision task that involves identifying and separating individual objects within an image, often by drawing boundaries around them.

The food image data was split into training and testing sets, and after the model was trained, the pre-labeled testing data was fed to the image classification model. Accuracy, Precision, Recall, and F-1 scores were calculated for the test data. The F1 score was defined as the harmonic mean of precision and recall. Accuracy was determined as the ratio of correctly predicted instances to the total instances. Precision was calculated as the ratio of true positives to the total predicted positives and recall was computed as the ratio of true positives to the total actual positives.

The next step in the computer vision pipeline was to pass the segmented images into a portion estimator. The segmented foods' portion was estimated using Python's Zoe Depth Estimation model.

Model Configuration

Traditional Expert System: Using a Python programming language, we designed a rule-based system with a set of predefined rules and logical inferences that uses data collected in the data collection stage to advise a user on what can be safely consumed or what needs to be removed from their plate, to adhere to Recommended Dietary Intakes. The traditional expert system used a dictionary as a data structure to represent a hypothetical stomach of a user, which contained foods they had eaten throughout the day.

LLM-augmented KG Question Answering: We utilized a pre-trained LLM, specifically Open-AI's Chat-GPT 3.5, and augmented it with a knowledge graph representing domain-specific relationships, such as the relationship between foods, a user's stomach, a user's medication, and chemical compounds found in food.

We created the knowledge graph using Neo4J software. Nodes in the knowledge graph represented entities such as the user, foods, chemical compounds, and medications. The Edges in the graph represent the relationship between the entities, and labels on the edges describe the type of relationship, such as “reacts with”, “contains,” and “ needs.”, “ate” e.t.c.

On starting the A.I system, a user provided their age, weight, height, activity level, and their sex. This information was automatically used to update the user profile in the knowledge graph. The user then proceeded to take a picture of the meal they desired to eat. The computer vision module performed image recognition and instance segmentation on the meal photograph and determined the portion of various foods in the meal. The names of the foods and their portions detected using the computer vision model were then used to perform a query on the knowledge graph.

Post query, after fetching data pertaining to the food nutrient information, chemical composition, and possible drug interactions from the knowledge graph, a simple decision tree was used to determine whether or not the user should consume the meal, it also provided possible solutions such as increasing or decreasing the portion of certain components of the meal, and waiting for a certain amount of time before consuming the meal, in the case of drug interactions.

We assessed five meals using the A.I system, and in each case, a report was generated for the user in natural English language. This report critically discussed how eating the meal could impact the user and what steps they could take regarding portioning.

The result of the report was then contrasted and compared with that written by the Knowledge Graph Augmented LLM after being fed the same information via a prompt.

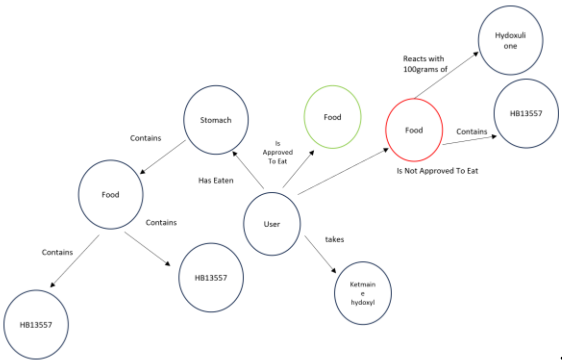
An Example of such a Prompt is:

"I am a 37 Year Old Female with Sickle Cell Disease. I have eaten 2 Plates of rice and 2 Chicken drumsticks today. I am about to eat 20g of Aprapransa and 10g of Meat for dinner, should I eat it?"

The information for the portioning and meal names is fed into the prompt string using data returned by the computer vision model.

Python's spaCy library was utilized to determine the similarity of the reports generated by the Traditional Expert System and that generated by the Knowledge-Graph Augmented Large Language Model.

SpaCy, with its comprehensive architecture, seamlessly blends linguistic rules, statistical modeling, and neural network techniques. It tokenizes input texts and applies a pipeline that includes part-of-speech tagging and named entity recognition. Additionally, SpaCy utilizes word embeddings to efficiently capture semantic information and relationships between words



Depiction of Knowledge Graph

REQUIREMENT ANALYSIS

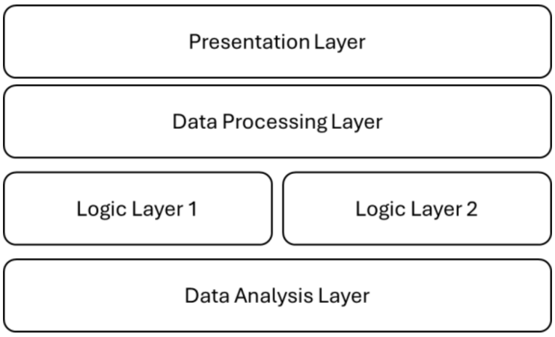
Architectural Requirements: Layered and Pipe Filter Design.

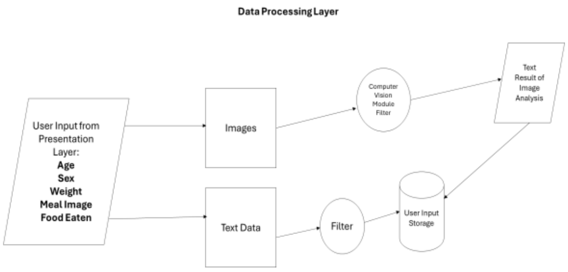
Data is collected in the presentation layer, which the user operates. The Data from the presentation layer is then sent to the first data processing layer, which uses a pipe and filter architecture.

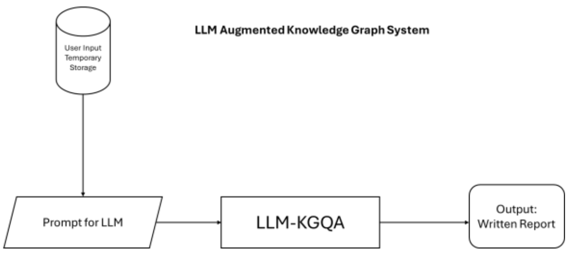
The pipe-filter architectural pattern operates by sequentially processing a data stream in a single direction. Data flows through the system as pipes transfer data to filters, with the output of one filter serving as the input for the subsequent one, thus forming a chain of data processing. [19]

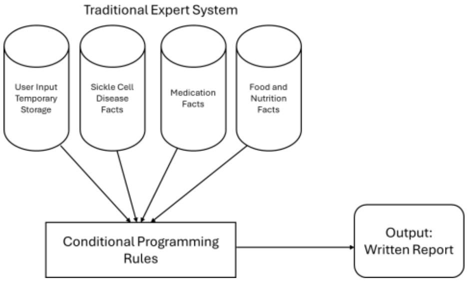
The data in the data processing layer is passed to the logic layers, namely, the Traditional expert system and the LLM-Augmented Knowledge graph system.

After the output is generated in the logic layers, it is passed to the data analysis layer to compare the two outputs.









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