

PROFESSIONAL TRAINING REPORT - II

entitled

Nutrition Detection Using Deep Learning And User Customize Nutrition Intake Planning

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering with
specialization in Internet of Things

by

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**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
SCHOOL OF COMPUTING**

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
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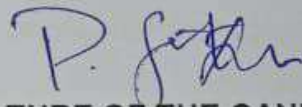
MAY 2024

DECLARATION

I, **Mr. Ponna srikar (41732030)**, hereby declare that the Professional Training Report-II entitled **"Nutrition detection using deep learning and user customize nutrition intake planning"** done by me under the guidance of **Mrs. K. Abinaya M.E**, is submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering degree in Computer Science and Engineering with specialization in Internet of Things.

DATE: 06/05/24

PLACE: Chennai



SIGNATURE OF THE CANDIDATE



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BONAFIDE CERTIFICATE

This is to certify that this Professional Training Report is the bonafide work of **Mr. Ponna srikar (41732030)** who carried out the project entitled "**Nutrition Detection Using Deep Learning And User Customize Nutrition Intake Planning**" under my supervision from January 2024 to May 2024.

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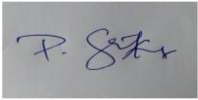
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I wish to express my thanks to all Teaching and Non-teaching staff members of the **Department of Computer Science and Engineering** who were helpful in many ways for the completion of the project.

COURSE CERTIFICATE

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Reporting Time	08:00 am	Gate Closure	09:30 am			
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ABSTRACT

The rise of computer vision and deep learning has garnered significant attention as a technology for the next generation to automate and reduce human efforts, offering unmatched benefits and minimising manual efforts in day to day life. Despite these advancements, most of health conscious people still weight there food manually for there food diet to be in control which is very difficult while maintaining the professional life. And due to the change in the life-style and food culture most humans are not attaining the daily nutritions (vitamin, protein other health supplement) which are essential for health, which may causes health problems like vitamin deficiency and many more concerning issue's. To address this issue, we propose the integration of "Image detection" technology to detection of food items and there amount of vitamin, protein ,fact other essential nutritions present in it, By estimating the weight of the detected food item's using the standard reference as coin. Based in the user age, weight, activity level, gender and height we can estimate the nutrition required for the user, which helps to acknowledge user for their food diet.

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CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Nutrition stands as a cornerstone of human health, exerting a profound influence on overall well-being and vitality. In today's bustling society, marked by hectic schedules and an overwhelming array of food choices, maintaining a balanced diet poses a formidable challenge for many individuals. Recognizing this pressing need, automated nutrition calculators have emerged as indispensable aids, leveraging technological innovations to provide personalized dietary recommendations tailored precisely to individual needs and preferences.

Our innovative system represents a significant leap forward in enhancing existing nutrition calculators by integrating cutting-edge image segmentation techniques with user-provided depth information. This unique fusion enables precise computations of food item volume and weight based on density, thereby establishing a robust foundation for accurate nutrition assessment. By tapping into a comprehensive repository of food nutrition data, our system generates bespoke recommendations that factor in user demographics and activity levels, ensuring a tailored and effective approach to dietary guidance.

Central to our methodology is a strong emphasis on user engagement and empowerment. We actively solicit demographic details such as age, weight, height, gender, and activity level from users to refine and personalize recommendations. Furthermore, our system employs intuitive graphical and numerical representations of nutrition intake, enabling users to easily comprehend and act upon the information provided. This emphasis on user-centric design fosters informed decision-making regarding dietary choices, empowering individuals to take charge of their health and wellness.

The cornerstone of our system's accuracy and efficiency lies in the utilization of the YOLOv8seg algorithm for image segmentation. Renowned for its prowess in identifying and delineating objects within complex scenes, this state-of-the-art

algorithm underpins robust food recognition capabilities. By seamlessly integrating image segmentation with depth information, our objective is to furnish users with a seamless and intuitive experience for tracking and managing their nutrition intake, thereby enabling them to proactively pursue healthier lifestyles.

In summary, our research represents a concerted effort to bridge the chasm between technology and nutrition, equipping individuals with indispensable tools to make informed dietary decisions and realize their wellness aspirations. Through the meticulous development and implementation of our nutrition calculator system, we aspire to empower users on their transformative journey toward enhanced health and well-being.

Expanding upon this initiative entails a deeper exploration of the profound significance of nutrition in fostering optimal health and addressing prevalent challenges in contemporary society. Additionally, elucidating the specific features and functionalities of our proposed system, with concrete examples demonstrating the efficacy of integrating image segmentation and depth information, will enrich the narrative. Furthermore, a thorough examination of the potential ramifications of our technology on individuals' dietary behaviors and long-term health outcomes will underscore the transformative potential of our approach. By delving into these facets, we aim to furnish a comprehensive understanding of the broader implications and practical applications of our innovative system in diverse real-world settings.

CHAPTER 2

LITERATURE REVIEW

2.1 SURVEY

The authors INGMAR WEBER and PALAKORN ACHANANUPARP attempted to acquire insights from machine-learning-based diet success prediction in order to assist people who are attempting to stay fit and healthy by tracking their dietary intake. The scientists studied the features of a failed diet using public food diaries from over 4,000 long-term active MyFitnessPal users. The authors used "quantified self" data to train a machine learning model to forecast being over or under self-set daily calorie goals repeatedly, and then looked at which features contributed to the model's prediction. The authors noticed that categorization is important. Performance was adequate, and the token-based model outperformed the category-based model, allowing for more in-depth data mining with such data.[1]

NANDISH SHAH and ISHANI SHAH proposed a healthy food habit and eating system based on web data mining, which would track eating habits and prescribe the forms of food that will promote health and avoid the types of food that will elevate the risk of sickness. To extract meaningful information about people's eating habits, the authors employed data mining algorithms such as classification, clustering, and association rules. Each food's nutritional structure was examined, as well as the fat, energy, and protein content. The percentage of vitamins in the dish was computed. The classification mining method was then used to evaluate the composition data and determine if the diet was healthy or not. As a consequence, each person was given personalized recommendations.[2]

Celestine Iwendi et al. (2020) investigate the data collection potential of their system. Machine and deep learning algorithms such as Naive Bayes, Logistic Regression, Multilayer Perceptron (MLP), Gated Recurrent Units (GRU), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) are the goals of this research framework and how they apply to IoMT data. For consideration in the clinical dataset, 30 people's information with 13 highlights of different illnesses, as well as 1000 things, were accumulated through the internet and hospitals. There are eight features in the

product area. Before applying deep learning and machine learning-based techniques, the characteristics of this IoMT data were examined and further encoded.[3]

Thi Ngoc Trang Tran et al. (2021) show that their method can be used to present a comprehensive review of healthcare recommender system research: Besides, our exploration recognizes from past important outlines concentrates that it gives knowledge for suggested circumstances and approaches. Dietary recommendations, drug ideas, health status forecasts, service recommendations, and recommendations from healthcare professionals are all included in this kind of proposal. They also give students examples from real-world situations to help them fully comprehend recommendation systems.[4]

Butti Gouthami and Malige Gangappa (2020) The USDA nutrition dataset will be used to determine the user's suggested diet. A set of grocery shop information that takes the user's preferred food intake into account. The USDA database contains nutritional data for every food item. A USDA ID is used as the baseline value for the input values for every 100 grams. Since they will ultimately be used to estimate the suggested diet, the data required to compute BMI (body mass index) must be provided. The second input utilized to determine the user's suggested diet is their daily food intake. The diet recommendation is initially created using the food that was eaten that day, and the input nutrient dataset is sorted by a nutritional deficit.[5]

Igor Orue Saiz et al. made an effort to find the research that has been done and the recommendation systems that have been used in the major databases for this purpose over the past five years. The results lead to the following conclusion: Previous works focus more attention on the recommendation system—typically collaborative filtering—than they do on the data or sample description; It is unknown which indices are used to calculate calories or nutrients. In this way, to be viable, it is basic to work with open information or all-around depicted information, which permits the experience to be rehashed by different gatherings, or at any rate to be comparable. [6]

CHAPTER 3

REQUIREMENTS ANALYSIS

3.1 OBJECTIVE OF THE PROJECT

- Due to the change in the life-style and food culture most humans are not attaining the daily nutritions (vitamin, protein other health supplement) which are essential for health, which may causes health problems like vitamin deficiency and many more concerning issue's.
- To address this issue, we propose the integration of "Image detection" technology to detection of food items
- There amount of vitamin, protein ,fact other essential nutritions present in it
- what are the missing daily essential nutrition. Which were not consumed by the user.

3.2 REQUIREMENTS

3.2.1 HARDWARE REQUIREMENTS

Compute Resources:

High-Performance Computing (HPC) Clusters: HPC clusters provide scalable computing resources for parallel processing and distributed computing tasks. They are suitable for training large deep learning models and conducting computationally intensive simulations.

Graphics Processing Units (GPUs): GPUs with high computational performance are essential for accelerating the training of deep learning models. NVIDIA GPUs such as the Tesla V100 or GeForce RTX series are commonly used for deep learning tasks due to their parallel processing capabilities and optimized software support.

Memory:

Random Access Memory (RAM): Deep learning models often require large amounts of memory to store data and intermediate computations during training and inference.

A minimum of 16GB of RAM is recommended for running deep learning experiments, with higher capacities beneficial for handling larger datasets and more complex models.

Storage:

Solid-State Drives (SSDs): SSDs offer fast read and write speeds, making them ideal for storing and accessing large datasets, model checkpoints, and intermediate results. SSDs provide low latency and high throughput compared to traditional hard disk drives (HDDs), resulting in faster data processing and model training.

Graphics Cards:

Graphics Processing Units (GPUs): Graphics cards with CUDA-enabled GPUs are essential for accelerating deep learning tasks such as model training and inference. NVIDIA GPUs are widely used in deep learning projects due to their extensive software support and optimized performance for deep learning frameworks.

Central Processing Unit (CPU):

Multicore CPU: A multicore CPU with multiple processing cores is necessary for general-purpose computing tasks, such as data preprocessing, model initialization, and inference. Modern CPUs from Intel or AMD offer sufficient computational power for running deep learning experiments and simulations.

Network Connectivity:

High-Speed Internet Connection: Reliable internet connectivity is essential for accessing online resources, downloading datasets, and collaborating with team members. A high-speed internet connection ensures efficient communication and data transfer, enabling seamless collaboration and remote work.

By meeting these software and hardware requirements, developers and researchers can effectively develop, deploy, and utilize DeepPLanx for infrastructure planning and design tasks, ensuring optimal performance and productivity throughout the project.

lifecycle. Adjustments may be made based on specific project needs, resource availability, and budget constraints.

3.2.2 SOFTWARE REQUIREMENTS

TensorFlow: TensorFlow is an open-source deep learning framework developed by Google. It offers a comprehensive ecosystem of tools and libraries for building, training, and deploying deep neural networks.

PyTorch: PyTorch is a popular deep learning framework known for its flexibility and ease of use. It provides dynamic computational graphs and a rich set of libraries for deep learning research and development.

Keras: Keras is a high-level neural networks API that runs on top of TensorFlow, Theano, or Microsoft Cognitive Toolkit (CNTK). It simplifies the process of building and training deep learning models with a user-friendly interface and modular design.

Programming Languages:

Python: Python is the primary programming language used in deep learning projects, thanks to its simplicity, readability, and extensive ecosystem of libraries. Proficiency in Python is essential for data preprocessing, model development, and implementation of DeepPLanx.

SQL: Structured Query Language (SQL) may be required for managing and querying databases containing architectural data, user preferences, and project specifications.

Data Visualization Tools:

Matplotlib: Matplotlib is a plotting library for Python that enables the creation of static, animated, and interactive visualizations. It is widely used for visualizing architectural drawings, building layouts, and model outputs.

Seaborn: Seaborn is a statistical data visualization library based on Matplotlib. It provides a high-level interface for drawing attractive and informative statistical graphics.

Plotly: Plotly is an interactive graphing library that allows users to create interactive plots and dashboards. It can be used to visualize complex architectural designs and explore 3D building models.

User Interface Frameworks:

PyQt: PyQt is a set of Python bindings for the Qt application framework. It allows developers to create cross-platform desktop applications with rich graphical user interfaces (GUIs) using the Qt Designer tool.

Tkinter: Tkinter is the standard GUI toolkit for Python. It provides a simple and easy-to-use interface for creating desktop applications with basic GUI components such as buttons, menus, and text boxes.

Dash: Dash is a Python framework for building analytical web applications. It enables the creation of interactive dashboards and data visualizations using Python, HTML, and CSS.

Version Control Systems:

Git: Git is a distributed version control system used for tracking changes in code repositories and coordinating collaborative development efforts. It provides features such as branching, merging, and conflict resolution, ensuring the integrity and reproducibility of the DeepPLanx project.

CHAPTER 4

DESIGN DESCRIPTION OF PROPOSED PROJECT

4.1 PROPOSED METHODOLOGY

The methodology of the proposed nutrition calculator system can be outlined as follows:

Image Segmentation: Food items are segmented from images using the YOLOv8seg algorithm, which is a state-of-the-art object detection algorithm capable of accurately identifying and delineating objects in images.

Isolated Mask Images - dal-curry_download-1-.jpg.rf.bb61007e405869453e889a1442741fec



Volume Calculation: The user provides depth information for each segmented food item, either manually or through depth-sensing technology. The system calculates the volume of each food item using the provided depth information.

$$\text{Food_volume} = (\text{food_area}) \times (\text{food_depth})$$

$$\text{Food_area} = (\text{sum_of_mask}(\text{pixel of food})) \times (\text{standard_refrence_ratio})$$

$$\text{standard_refrence_ratio} = (\text{original_coin_area}) / (\text{pixel_coin_area})$$

$$=((\pi) \times (r^2)) / (\text{sum_of_mask}(\text{pixel of coin}))$$

$$\text{FoodArea} = \sum_{i,j=0}^{i,j<640} \text{maskfood}_{i,j} \left[\frac{\text{OriginalCoinArea}}{(\sum_{i,j=0}^{i,j<640} \text{maskcoin}_{i,j})} \right]$$

Weight Estimation: Food density data is used to estimate the weight of each food item based on its volume. The system accesses a database containing food density information to perform this calculation.

$$\text{Food_weight} = (\text{food_volume}) \times (\text{food_density}(\text{gm/ml}))$$

Nutrition Retrieval and Estimation: Nutrition information for each food item is retrieved from a comprehensive database containing the nutritional composition of various foods. This database includes information such as calories, macronutrients (protein, carbohydrates, fat), vitamins, and minerals.

The Nutrition of the food is calculated by estimating the weight of the food and Nutrition database (which contain's density(gm/ml) of the food , nutrition per 1gm of the food)

$$\text{Amount of nutrition} = (\text{food_weight}) \times (\text{nutrition_per_1gm})$$

User Input: The system prompts the user to provide demographic information, including name, age, weight, height, gender, and activity level. The user's activity level is classified into categories such as sedentary, lightly active, moderately active, very active, and extra active, each corresponding to a specific multiplier applied to Total Daily Energy Expenditure (TDEE).

One commonly used formula to estimate total daily energy expenditure (TDEE), which includes both basal metabolic rate (BMR) and activity level, is the Mifflin-St Jeor Equation. The equation is as follows:

For men:

$$[\text{TDEE} = (10 \text{ times weight in kg}) + (6.25 \text{ times height in cm}) - (5 \text{ times age in years}) + 5]$$

For women:

[$TDEE = (10 \text{ times weight in kg}) + (6.25 \text{ times height in cm}) - (5 \text{ times age in years}) - 161$]

Once you have estimated TDEE, you can adjust it based on activity level using the following multipliers:

- Sedentary (little to no exercise): $TDEE \times 1.2$
- Lightly active (light exercise/sports 1-3 days/week): $TDEE \times 1.375$
- Moderately active (moderate exercise/sports 3-5 days/week): $TDEE \times 1.55$
- Very active (hard exercise/sports 6-7 days a week): $TDEE \times 1.725$
- Extra active (very hard exercise/sports & physical job or 2x training): $TDEE \times 1.9$

Nutrition Recommendation: Based on the user's input and calculated nutrition intake, personalized nutrition recommendations are generated. These recommendations take into account the user's demographic information, activity level, and nutritional needs. The system provides graphical and numerical representations of the user's consumed nutrition and compares it to the recommended intake, highlighting any deficiencies or excesses.

To estimate the intake of various nutrients based on the Total Daily Energy Expenditure (TDEE) calculated using the Mifflin-St Jeor Equation, we can use general recommendations for the distribution of macronutrients (carbohydrates, fats, and proteins) and the recommended daily intake of certain micronutrients.

1. ****Total Fat, Saturated Fat, Polyunsaturated Fat, and Monounsaturated Fat**:**

- Total Fat: Generally, 20-35% of total daily calories come from fat.

- Saturated Fat: Less than 10% of total daily calories come from saturated fat.
- Polyunsaturated Fat: Up to 10% of total daily calories come from polyunsaturated fat.
- Monounsaturated Fat: Up to 20% of total daily calories come from monounsaturated fat.

2. **Cholesterol and Sodium**:

- Cholesterol: Less than 300 mg per day.
- Sodium: Less than 2,300 mg per day, or less than 1,500 mg per day for certain groups.

3. **Total Carbohydrates and Dietary Fiber**:

- Total Carbohydrates: Approximately 45-65% of total daily calories come from carbohydrates.
- Dietary Fiber: 25 grams per day for women, 38 grams per day for men.

4. **Sugars**:

- Less than 10% of total daily calories come from added sugars.

5. **Protein**:

- Protein: Approximately 10-35% of total daily calories come from protein, with specific requirements based on age, weight, and activity level.

6. **Micronutrients (Calcium, Iron, Potassium)**:

- Refer to the Dietary Reference Intakes (DRIs) for specific age and gender groups to determine the recommended daily intake of calcium, iron, and potassium.

Based on these recommendations and your estimated TDEE of approximately 1638.75 calories per day, you can calculate the estimated intake of each nutrient. For example, if you aim for 30% of your calories to come from fat, you would calculate:

- Total Fat (g) = (30% of 1638.75 calories) / 9 calories per gram of fat (approximate)

- Similarly, you can calculate the intake of other nutrients based on their respective recommendations and your estimated TDEE. Remember that these calculations provide estimates and may need to be adjusted based on individual preferences, dietary restrictions, and health goals. Consulting with a registered dietitian can provide personalized recommendations tailored to your specific needs.

```
graph LR; Input1([image-input]) --> Model[yolov8seg model]; Model --> Output1[model-output]; Output1 --> Step1[gives the amount of nutrition present in food]; Input2([user data input]) --> Step2[calculate the user nutrition requirements]; DB[(data-base)] -- "nutrition value of food items" --> Step1; Step1 --> Final[give's the deficiency/over consumption food nutrition]; Step2 --> Final;
```

4.1.2 Various Stages

- **Food Image Dataset:** Gather a diverse dataset of food images representing various types of meals, dishes, and ingredients.
- **Nutritional Data:** Collect nutritional information for each food item, including vitamins, proteins, fats, and other essential nutrients.

2. Image Detection and Segmentation:

- **Object Detection Model:** Develop or use pre-trained deep learning models (e.g., Faster R-CNN, YOLO) for food item detection within images.
- **Segmentation:** Implement techniques to segment detected food items from the background for precise analysis.

3. Nutritional Analysis:

- **Weight Estimation:** Utilize a standard reference object (e.g., coin) placed alongside food items to estimate their weights based on image analysis.
- **Nutrient Quantification:** Apply image processing algorithms to estimate the amount of essential nutrients (vitamins, proteins, fats) present in each food item.

4. User Profile and Nutrition Calculation:

- **User Inputs:** Collect user-specific information including age, weight, activity level, gender, and height.
- **Nutritional Requirements Estimation:** Calculate personalized nutritional requirements based on user inputs using established dietary guidelines or formulas.

5. Integration and Interface Development:

- **System Integration:** Integrate the image detection, nutritional analysis, and user profile components into a cohesive system.
- **User Interface:** Develop a user-friendly interface (e.g., mobile app, web application) for users to interact with the system, input personal details, and receive nutritional recommendations.

6. Model Training and Validation:

- **Deep Learning Training:** Train and fine-tune the object detection and nutrient estimation models using the collected dataset.
- **Validation and Testing:** Evaluate the performance of the integrated system through rigorous testing and validation, ensuring accurate food detection and nutrient estimation.

7. Personalized Nutrition Recommendations:

- **Nutrition Insights:** Present personalized nutrition insights to users based on their dietary preferences, lifestyle, and nutritional requirements.

- **Recommendation Engine:** Implement a recommendation engine that suggests balanced meal options and dietary adjustments to meet specific nutritional goals.

8. Evaluation and Iterative Improvement:

- **User Feedback:** Gather feedback from users to assess the usability, effectiveness, and accuracy of the system.
- **Continuous Enhancement:** Iterate on the system based on feedback and emerging technologies to enhance performance and user satisfaction over time.

4.1.4 working principles

Food_valume=(food_area)X(food_depth)

Food_area=(sum_of_mask(pixel of food))X(standard_refrence_ratio)

standard_refrence_ratio= (original_coin_area)/(pixel_coin_area)

=((pi)X(r^2))/(sum_of_mask(pixel of coin))

$$FoodArea = \sum_{i,j=0}^{i,j<640} maskfood_{i,j} \left[\frac{OriginalCoinArea}{(\sum_{i,j=0}^{i,j<640} maskcoin_{i,j})} \right]$$

Food_weight.=(food_valume)X(food_density(gm/ml))

Amount of nutrition=(food_weight)X(nutrition_per_1gm)

For men:

[TDEE = (10 times weight in kg) + (6.25 times height in cm) - (5 times age in years) + 5]

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Once you have estimated TDEE, you can adjust it based on activity level using the following multipliers:

- Sedentary (little to no exercise): TDEE x 1.2
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- Moderately active (moderate exercise/sports 3-5 days/week): TDEE x 1.55

- Very active (hard exercise/sports 6-7 days a week): $TDEE \times 1.725$
- Extra active (very hard exercise/sports & physical job or 2x training): $TDEE \times 1.9$

4.2 FEATURES

1. Food Image Detection and Recognition:

- **Object Detection:** Utilize deep learning-based object detection models to accurately detect and localize food items within images.
- **Food Categorization:** Classify detected food items into specific categories (e.g., fruits, vegetables, grains) to facilitate subsequent nutritional analysis.

2. Nutritional Analysis and Estimation:

- **Weight Estimation:** Implement computer vision techniques to estimate the weight of detected food items using a standard reference object (e.g., coin) for calibration.
- **Nutrient Quantification:** Develop algorithms to estimate the amount of essential nutrients (e.g., vitamins, proteins, fats) present in each recognized food item based on its weight and category.

3. User Profile Management:

- **Personalized Input:** Allow users to input personal details such as age, weight, height, gender, and activity level to customize nutritional recommendations.
- **Nutritional Requirements Calculation:** Calculate personalized nutritional requirements based on user-specific factors using established dietary guidelines or formulas.

4. Interactive User Interface:

- **User-Friendly Design:** Design an intuitive and visually appealing user interface (UI) accessible via mobile app or web application.

- **Input and Feedback:** Enable users to input food images, view nutritional analyses, and receive tailored recommendations in a clear and understandable format.

5. Personalized Nutrition Recommendations:

- **Goal Setting:** Allow users to set specific dietary goals (e.g., weight loss, muscle gain, general health improvement) within the application.
- **Recommendation Engine:** Develop a recommendation engine that suggests balanced meal options and dietary adjustments to help users meet their nutritional goals.

6. Data Privacy and Security:

- **Secure Data Handling:** Implement robust data privacy and security measures to protect user information and maintain confidentiality.
- **Compliance:** Ensure compliance with relevant data protection regulations (e.g., GDPR, HIPAA) to build user trust and confidence in the system.

7. Model Training and Optimization:

- **Continuous Learning:** Continuously update and optimize the deep learning models used for food detection and nutrient estimation based on new data and user feedback.
- **Performance Monitoring:** Implement mechanisms to monitor and evaluate the performance of the system, including accuracy of food recognition and nutritional analysis.

8. Feedback and Iterative Improvement:

- **User Feedback Loop:** Solicit and incorporate user feedback to identify areas for improvement and enhance the overall user experience.
- **Iterative Development:** Adopt an iterative development approach to iteratively enhance features, address usability issues, and introduce new functionalities based on user needs.

CHAPTER 5

RESULTS AND DISCUSSION

The integration of image detection technology for food recognition combined with nutritional analysis represents a promising approach to improving dietary management and health awareness. By leveraging computer vision algorithms, this system can accurately identify various food items from images, allowing users to conveniently track their nutritional intake without manual data entry. Estimating food weight using standard references provides additional context for portion sizes, enhancing the accuracy of nutrient calculations. Coupled with user-specific information like age, weight, activity level, gender, and height, personalized nutritional recommendations can be generated to guide individuals towards meeting their dietary needs. Despite potential challenges such as food variability and accuracy in object detection, ongoing advancements in machine learning can address these issues, paving the way for a more seamless integration of technology into daily health routines. Looking ahead, the continuous refinement of these systems, potential integration with wearable devices for real-time monitoring, and the generation of behavioral insights can further empower individuals to make informed and healthier food choices, ultimately contributing to improved overall well-being.

The below data contains nutrition data of individual food item

ITEM*(100gm)	0 dal-curry	1 rice
Calories	191.60134906110125	72.08944471718543
Total Fat(g)	3.6740431267708775	0.1673903515104925
Saturated Fat(g)	0.5511064690156317	0.055796783836830836
Polyunsaturated Fat(g)	0.5511064690156317	0.055796783836830836
Monounsaturated Fat(g)	2.2044258760625266	0.055796783836830836
Cholesterol(mg)	0.0	0.0
Sodium(mg)	372.1805687418899	0.5579678383683083
Total Carbohydrates(g)	29.39234501416702	15.846286609659956
Dietary Fiber(g)	11.205831536651175	0.22318713534732335
Sugars(g)	3.8577452831094217	0.055796783836830836
Protein(g)	12.124342318343896	1.5065131635944327
Calcium(mg)	38.026346362078584	5.635475167519914
Iron(mg)	4.959958221140685	0.66956140604197
Potassium(mg)	615.7696280467991	19.41728077521713

The below data contains Total nutrition data present in the food items

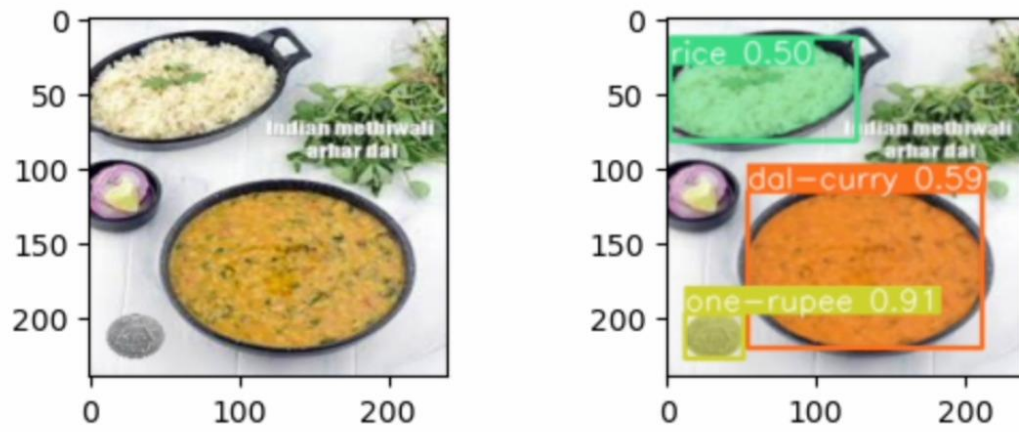
ITEM*(100gm)	0 Total
Calories	263.690794
Total Fat(g)	3.841433
Saturated Fat(g)	0.606903
Polyunsaturated Fat(g)	0.606903
Monounsaturated Fat(g)	2.260223
Cholesterol(mg)	0.0
Sodium(mg)	372.738537
Total Carbohydrates(g)	45.238632
Dietary Fiber(g)	11.429019
Sugars(g)	3.913542
Protein(g)	13.630855
Calcium(mg)	43.661822
Iron(mg)	5.62952
Potassium(mg)	635.186909

4.3 Predicted nutrition values

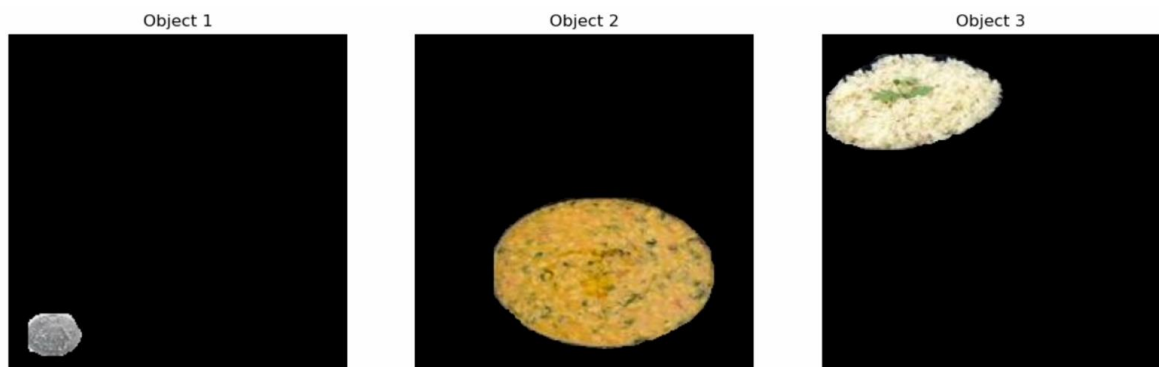
The below data contains the required amount of nutrition based on user data

Calories: 2540.0625
Total Fat(g): 84.66874999999999
Saturated Fat(g): 28.22291666666667
Polyunsaturated Fat(g): 28.22291666666667
Monounsaturated Fat(g): 42.334374999999994
Cholesterol(mg): 200
Sodium(mg): 1500
Total Carbohydrates(g): 285.75703125
Dietary Fiber(g): 38
Sugars(g): 63.501562500000006
Protein(g): 63.501562500000006
Calcium(mg): 1000

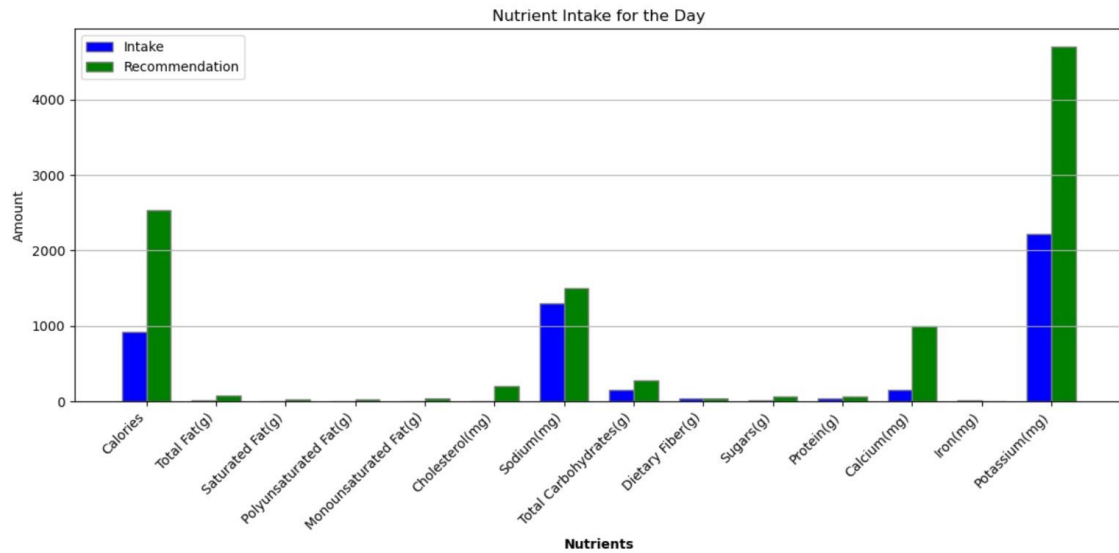
4.4 Estimated user intake plane



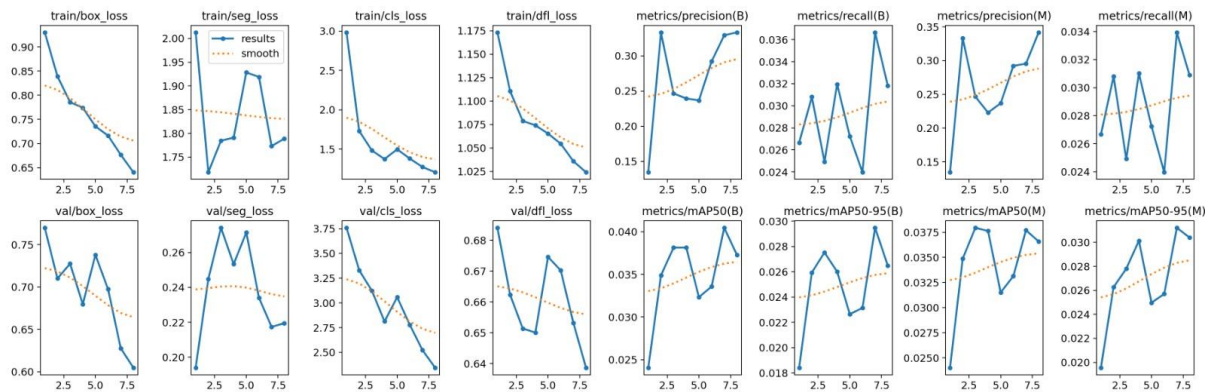
4.5 Predicted output



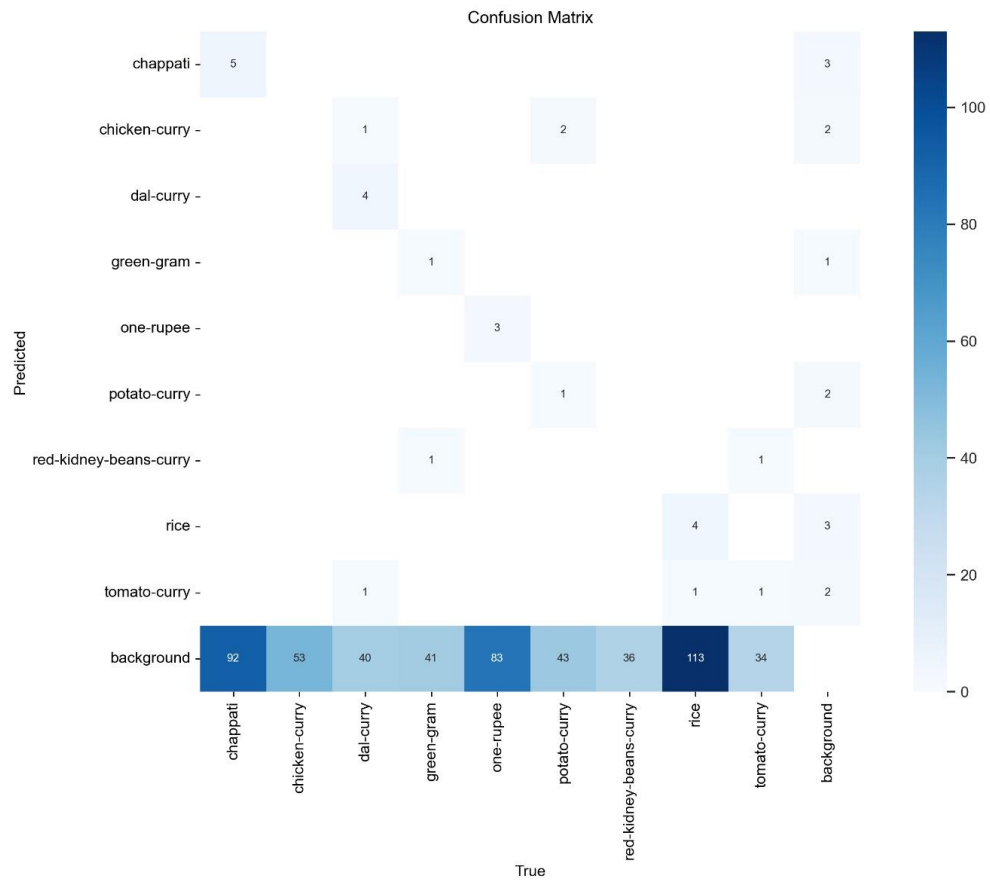
4.6 Food segmentation



4.7 Nutrition intake VS daily consumption



4.8 Training Result's



4.9 Confusion Matrix

CONCLUSION

In conclusion, the proposed nutrition calculator system offers a novel and efficient method for tracking and managing nutrition intake. By leveraging image segmentation techniques, depth information, food density data, and a comprehensive nutrition database, the system provides accurate and personalized nutrition recommendations tailored to the individual needs and preferences of the user. The graphical and numerical representations of nutrition intake facilitate easy understanding and interpretation, empowering users to make informed dietary choices and maintain a balanced diet for optimal health and well-being. Future research may focus on further refining the segmentation and volume calculation algorithms, expanding the database of food nutrition information, and incorporating additional features to enhance the user experience. This introduction outlines the motivation behind the research, introduces the proposed system, and provides an overview of the methodology. It sets the stage for the subsequent sections of the research paper.

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APPENDIX

A. Research Paper

Nutrition detection using deep learning and user customize nutrition intake planning

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Abstract— The rise of computer vision and deep learning has garnered significant attention as a technology for the next generation to automate and reduce human efforts, offering unmatched benefits and minimising manual efforts in day to day life.

Despite these advancements, most of health conscious people still weight there food manually for there food diet to be in control which is very difficult while maintaining the professional life. And due to the change in the life-style and food culture most humans are not attaining the daily nutritions (vitamin, protein other health supplement) which are essential for health, which may causes health problems like vitamin deficiency and many more concerning issue's.

To address this issue, we propose the integration of "Image detection" technology to detection of food items and there amount of vitamin, protein ,fact other essential nutritions present in it, By estimating the weight of the detected food item's using the standard reference as coin.

Based in the user age, weight, activity level, gender and height we can estimate the nutrition required for the user, which helps to acknowledge user for their food diet.

Introduction

Nutrition is a cornerstone of human health, impacting every facet of well-being. Yet, in today's fast-paced world, many individuals struggle to maintain a balanced diet amidst hectic

schedules and a plethora of food choices. Automated nutrition calculators have emerged as valuable tools in navigating this challenge, leveraging technological advancements to provide personalized recommendations tailored to individual dietary needs and preferences.

Our proposed system aims to enhance the capabilities of existing nutrition calculators by integrating image segmentation techniques with depth information provided by users. This integration enables the accurate calculation of food item volume and weight based on density, laying the groundwork for precise nutrition assessment. By leveraging a comprehensive database of food nutrition information, our system generates tailored recommendations, taking into account user demographics and activity level.

Central to our approach is the emphasis on user engagement and empowerment. By prompting users to provide demographic information such as age, weight, height, gender, and activity level, we ensure that recommendations are personalized to their specific needs. Moreover, our system provides intuitive graphical and numerical representations of nutrition intake, enabling users to easily interpret and act upon the information presented

The utilization of the YOLOv8seg algorithm for image segmentation serves as a foundation for the accuracy and efficiency of our system. This state-of-the-art algorithm excels

in identifying and delineating objects within complex scenes, providing a robust framework for food recognition. By harnessing the power of image segmentation, coupled with depth information, we aim to offer users a seamless and intuitive experience in tracking and managing their nutrition intake.

In summary, our research endeavors to bridge the gap between technology and nutrition, offering individuals the tools they need to make informed dietary choices and achieve their wellness goals. Through the development and implementation of our nutrition calculator system, we seek to empower users in their journey towards better health and well-being.

Related Works

Nowadays, a human being faces a variety of health issues, including fitness issues, improper diet, mental health issues, and so on. Various studies show that improper and inadequate dietary intake is a primary cause of a variety of health problems and diseases.

Our proposed system aims to enhance the capabilities of existing nutrition calculators by integrating image segmentation techniques with depth information provided by users. This integration enables the accurate calculation of food item volume and weight based on density, laying the groundwork for precise nutrition assessment. By leveraging a comprehensive database of food nutrition information, our system generates tailored recommendations, taking into account user demographics and activity level. Our research endeavors to bridge the gap between technology and nutrition, offering individuals the tools they need to make informed dietary choices and achieve their wellness goals. Through the development and implementation of our nutrition calculator system, we seek to empower users in their journey towards better health and well-being. These areas present prospects for further growth and improvement.

Vitamin Deficiency and Food Recommendation System Using Machine Learning, developed by Ms. A.Bhavana[1] , Objective of this project is to create a vitamin dataset with deficient and non-deficient values and train model using multiple machine learning algorithms and then predict food recommendation based on result from vitamin deficiency values .

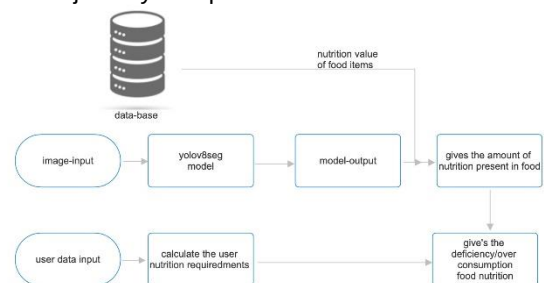
DIET RECOMMENDATION SYSTEM USING MACHINE LEARNING , developed by Reema Golagana[2] , The machine learning and deep learning algorithms used in this study framework include Random Forest, K-Means, and Long Short-Term Memory (LSTM). To predicts the meal plan based on the user's dietary nutritional requirements. It could achieve a personalized diet plan for individuals and help individuals lead healthier lives.

A new approach for recommending healthy diet using predictive data mining algorithm their developed by Vijay Jaiswal[3] , Their implementation showed that the decision tree learning algorithm, RandomTree works well on any classification problems having a dataset with the non-repeated values.

Review On Diet Recommendation System Using Machine Learning developed by Trupti Bhagat,[4] He used Decision Tree Algorithm will helps to get the appropriate results as compared to other one the proposed mechanism will be workout not only with diet recommendation but it is also differ by the technique and terminology we are using

System Architecture

The proposed system architecture integrates user input of demographic information such as age, weight, height, gender, and activity level with image acquisition and processing using advanced segmentation techniques like YOLOv8seg, augmented by depth information for accurate volume and weight estimation of food items. Leveraging a comprehensive nutrition database, the system calculates personalized nutritional recommendations based on identified food items and user demographics. A user-friendly interface presents graphical and numerical representations of nutrition intake, facilitating informed dietary decisions. Continuous feedback mechanisms ensure system refinement, ultimately empowering users to navigate their wellness journey with precision



The system architecture of our proposed nutrition calculator revolves around addressing the challenges individuals face in maintaining a balanced diet amidst modern lifestyles. Leveraging automated nutrition calculators, we aim to integrate cutting-edge image segmentation techniques with user-provided depth information to accurately assess food item volume and weight, thereby enabling precise nutrition evaluation. This integration, coupled with a comprehensive database of food nutrition information, forms the backbone of our system, allowing for the generation of tailored recommendations tailored to individual demographics and activity levels. Key to our approach is user engagement and empowerment, facilitated by prompts for demographic details and intuitive graphical representations of nutrition intake. The utilization of advanced algorithms such as YOLOv8seg ensures the accuracy and efficiency of food recognition within complex scenes, enhancing the user experience in managing their nutrition intake seamlessly. Ultimately, our system endeavors to bridge the gap between technology and nutrition, equipping individuals with the necessary tools to make informed dietary choices and achieve their wellness

goals, thus fostering better health and well-being.

Implementation Details(dataset, data, model, implementation module)

1. **Image Segmentation:** Food items are segmented from images using the YOLOv8seg algorithm, which is a state-of-the-art object detection algorithm capable of accurately identifying and delineating objects in images.
2. **User Input:** The system prompts the user to provide demographic information, including name, age, weight, height, gender, and activity level. The user's activity level is classified into categories such as sedentary, lightly active, moderately active, very active, and extra active, each corresponding to a specific multiplier applied to Total Daily Energy Expenditure (TDEE).
3. **Volume Calculation:** The user provides depth information for each segmented food item, either manually or through depth-sensing technology. The system calculates the volume of each food item using the provided depth information.
4. **Weight Estimation:** Food density data is used to estimate the weight of each food item based on its volume. The system accesses a database containing food density information to perform this calculation.

$$\text{Food_weight} = (\text{food_volume}) \times (\text{food_density}(\text{gm/ml}))$$

5. **Nutrition Retrieval and Estimation:** Nutrition information for each food item is retrieved from a comprehensive database containing the nutritional composition of various foods. This database includes information such as calories, macronutrients (protein, carbohydrates, fat), vitamins, and minerals.

The Nutrition of the food is calculated by estimating the weight of the food and Nutrition database(which contain's density(gm/ml) of the food , nutrition per 1gm of the food)

$$\text{Amountofnutrition} = (\text{food_weight}) \times (\text{nutrition_per_1gm})$$

6. **Nutrition Recommendation:** Based on the user's input and calculated nutrition intake, personalized nutrition recommendations are generated. These recommendations take into account the user's demographic information, activity level, and nutritional

needs. The system provides graphical and numerical representations of the user's consumed nutrition and compares it to the recommended intake, highlighting any deficiencies or excesses.

Discussion and Future Work

Your proposed system sounds like a promising approach to addressing the challenges of maintaining a balanced diet in today's fast-paced world. Integrating image segmentation techniques with depth information to accurately calculate food item volume and weight is a novel idea that could significantly enhance the precision of nutrition assessment. Additionally, leveraging a comprehensive database of food nutrition information and personalizing recommendations based on user demographics and activity level demonstrates a commitment to tailoring solutions to individual needs.

The emphasis on user engagement and empowerment is crucial, as it ensures that users actively participate in the process of managing their nutrition intake. By prompting users to provide demographic information and offering intuitive graphical and numerical representations of nutrition intake, your system facilitates understanding and encourages informed decision-making.

The utilization of the YOLOv8seg algorithm for image segmentation appears to be a sound choice, given its reputation for accuracy and efficiency in object detection within complex scenes. Leveraging this state-of-the-art algorithm should contribute to the reliability and usability of your system.

As for future work, there are several avenues for further enhancement and refinement. For instance, continuously updating and expanding the database of food nutrition information will ensure that recommendations remain relevant and accurate. Additionally, incorporating machine learning techniques to improve the system's ability to adapt to individual preferences and dietary patterns could further enhance its effectiveness. Moreover, considering the integration of wearable devices or other sensors to capture real-time data on physical activity and physiological parameters could provide valuable insights for personalized recommendations.

Overall, your research endeavors hold promise in bridging the gap between technology and nutrition, offering individuals valuable tools to support their journey towards better health and well-being. Continued development and refinement of your nutrition calculator system could have a significant impact on empowering users to make informed dietary choices and achieve their wellness goals.

Conclusion

In conclusion, the proposed nutrition calculator system offers a novel and efficient method for tracking and managing

nutrition intake. By leveraging image segmentation techniques, depth information, food density data, and a comprehensive nutrition database, the system provides accurate and personalized nutrition recommendations tailored to the individual needs and preferences of the user. The graphical and numerical representations of nutrition intake facilitate easy understanding and interpretation, empowering users to make informed dietary choices and maintain a balanced diet for optimal health and well-being. Future research may focus on further refining the segmentation and volume calculation algorithms, expanding the database of food nutrition information, and incorporating additional features to enhance the user experience.

This introduction outlines the motivation behind the research, introduces the proposed system, and provides an overview of the methodology. It sets the stage for the subsequent sections of the research paper.

References

Some of the references that helped us in our project are:

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B.Source Code

Data (example values, replace with actual data)

```
def plot(user_intake,required):
```

```
    nutrients = ['Calories', 'Total Fat(g)', 'Saturated Fat(g)', 'Polyunsaturated Fat(g)',
                 'Monounsaturated Fat(g)', 'Cholesterol(mg)', 'Sodium(mg)',
                 'Total Carbohydrates(g)', 'Dietary Fiber(g)', 'Sugars(g)',
                 'Protein(g)', 'Calcium(mg)', 'Iron(mg)', 'Potassium(mg)']
```

```
    intake = user_intake # Intake values
```

```
    min_recommendations = required[0] # Minimum recommended intake values
```

```
    # Number of nutrients
```

```
    num_nutrients = len(nutrients)
```

```
    # Width of each bar
```

```
    bar_width = 0.35
```

```
    # Set the positions of the bars on the x-axis
```

```
    r1 = np.arange(num_nutrients)
```

```
    r2 = [x + bar_width for x in r1]
```

```
    # Plotting
```

```
    plt.figure(figsize=(12, 6)) # Adjust the figure size as needed
```

```
    plt.bar(r1, intake, color='b', width=bar_width, edgecolor='grey', label='Intake')
```

```
    plt.bar(r2, min_recommendations, color='g', width=bar_width, edgecolor='grey',
label='Recommendation')
```

```
    # Adding labels and title
```

```
    plt.xlabel('Nutrients', fontweight='bold')
```

```
    plt.xticks([r + bar_width/2 for r in range(num_nutrients)], nutrients, rotation=45, ha='right') # Rotate
labels for better visibility
```

```
    plt.ylabel('Amount')
```

```
    plt.title('Nutrient Intake for the Day')
```

```
    # Adding legend
```

```
    plt.legend()
```

```
    # Show plot
```

```

plt.grid(axis='y')
plt.tight_layout() # Adjust layout to prevent overlap
plt.show()

from ultralytics import YOLO
from pathlib import Path

import cv2
import numpy as np

import matplotlib.pyplot as plt
from PIL import Image
import matplotlib.image as mpimg
from rich import print as Print
import pandas as pd
def show_img(img):
    plt.imshow(mpimg.imread(img))
def show_result(result):
    plt.imshow(Image.fromarray(result[0].plot()[::-1]))

def required_cal(user_data):
    activity=[1.2, 1.375, 1.55, 1.725, 1.9]
    nutrition=[0]*14
    if user_data[2]:
        cal=(10*user_data[3])+(6.25*user_data[4])-(5*user_data[1])+5
        # return cal*activity[user_data[5]-1],user_data[0]
        nutrition[0]=cal
        nutrition[8]=38

    else:
        cal=(10*user_data[3])+(6.25*user_data[4])-(5*user_data[1])-161
        # return cal*activity[user_data[5]-1],user_data[0]
        nutrition[0]=cal
        nutrition[8]=25
    nutrition[0]=nutrition[0]*activity[user_data[5]]
    nutrition[1]=nutrition[0]*0.3/9

```

```

nutrition[2]=nutrition[0]*0.1/9
nutrition[3]=nutrition[0]*0.1/9
nutrition[4]=nutrition[0]*0.15/9
nutrition[5]=200
nutrition[6]=1500
nutrition[7]=nutrition[0]*0.45/4
nutrition[9]=nutrition[0]*0.025
nutrition[10]=nutrition[0]*0.025
nutrition[11]=1000
nutrition[12]=8
nutrition[13]=4700
return (nutrition,user_data)

```

```
def display_masks_and_area(result):
```

```

    data = [] # List to store class name, confidence, and area data
    for r in result:
        img = np.copy(r.orig_img)
        img_name = Path(r.path).stem

        # Create a subplot for each object
        num_objects = len(r)
        fig, axes = plt.subplots(1, num_objects, figsize=(num_objects * 5, 5))

        # Iterate each object contour
        for ci, c in enumerate(r):
            label = c.names[c.bboxes.cls.tolist()].pop()
            confidence = c.bboxes.conf.tolist().pop() # Adjusted this line

            b_mask = np.zeros(img.shape[:2], np.uint8)

            # Create contour mask
            contour = c.masks.xy.pop().astype(np.int32).reshape(-1, 1, 2)
            _ = cv2.drawContours(b_mask, [contour], -1, (255, 255, 255), cv2.FILLED)

            # Isolate object with black background
            mask3ch = cv2.cvtColor(b_mask, cv2.COLOR_GRAY2BGR)

```

```

isolated = cv2.bitwise_and(mask3ch, img)

# Calculate area
hull = cv2.convexHull(contour)
area = cv2.contourArea(hull)
class_name = label

# Print and store data
print(f"Class: {class_name}, Confidence: {confidence}, Object {ci} area (in pixels): {area}")
data.append([class_name, confidence, area])

# Display the isolated mask image in subplot
axes[ci].imshow(cv2.cvtColor(isolated, cv2.COLOR_BGR2RGB))
axes[ci].set_title(f"Object {ci + 1}")
axes[ci].axis('off')

plt.suptitle(f"Isolated Mask Images - {img_name}")
plt.show()

return data
def volume(data):
    coin='one-rupee'
    coin_data=[x for x in data if x[0]==coin]
    if not any(coin_data):
        print(f'coin data is not found')
        return
    print(f'coin_data{coin_data}')
    coin_area_ratio=(1.15*3.14*1.15)/coin_data[0][2]

    print(f'coin data :{coin_data}')
    food_data=[x for x in data if x[0]!=coin and x[0]!='chappati']
    vol=[]
    if 'chappati' in data[:,0]:
        print(f'enter the number of chappati\'s')
        depth=int(input())
        vol=vol+[['chappati',depth]]

```

```

for item in food_data:
    Print(f'[green]enter the approx depth for {item[0]}')
    depth=int(input())

    volume=coin_area_ratio*item[2]*depth
    vol=vol+[[item[0],volume]]

return vol

def nurtition(df,vol):
    if vol is None:
        print('The volume of the input is None')
        return None

    item = [(x, np.array(j)) for x in vol
            for j in df.itertuples(index=False)
            if x[0] == j[0]]

    # np.concatenate((array1, array2), axis=0)
    result=[np.concatenate([(j[0]),[float(k)*(float(i[1])*float(j[1])/100) for k in j[2:]]],axis=0) for i,j in item]
    # result=[np.concatenate([(j[0]),[float(k)*(float(i[1])*float(j[1])/100) for k in j[2:]]],axis=0) for i,j in item]
    return result

def total_nutrition(df):
    numeric_columns=df.columns[1:]
    df[numeric_columns]=df[numeric_columns].apply(pd.to_numeric)
    df.iloc[:,0]='Total'
    column_sums=df.sum()
    column_sums.iloc[:,0]="Total"
    df_new=pd.DataFrame(column_sums.iloc[:,].values.tolist(),df.columns)
    return df_new.transpose()

def pipe_line(img):
    model = YOLO('/Users/srikar/pytorch-test/yolov8/runs/segment/train2/weights/best.pt')
    result=model(img)
    plt.subplot(2, 2, 1)
    show_img(img)
    plt.subplot(2, 2, 2)

```

```

show_result(result)
# plt.subplot(2, 2, 3)
data=display_masks_and_area(result)
plt.show
vol=volume(data)
Print(f'[bold][red]vol_data: ',f'[bold][green]{vol} \n',f'[bold][red]data_food_item: ',f'[bold][green]{data}')
df=pd.read_csv('fullfill.1.0.4.csv')
test=nurtition(df,vol)
df_names=np.array(df.columns)
df_names=np.concatenate((df_names[0],df_names[2:]),axis=0)
test=np.array(test)
new_test=test.reshape(-1,15)
test_df=pd.DataFrame(new_test,columns=df_names)
print('\n\n')
Print("[bold][purple]The below data contains nutrition data of individul food item")
print(test_df.head().transpose())
print('\n\n')
Print("[bold][purple]The below data contains Total nutrition data present in the food items")
user_intake=total_nutrition(test_df).values
print(total_nutrition(test_df).transpose())
user_data=[0]*6 #name,age,gender,weigth,height,activity_level
Print("[bold][green] enter the user name")
user_data[0]=input()
Print("[bold][green] enter the user age")
user_data[1]=int(input())
Print("[bold][green] enter the user gender(male:1 , female:0)")
user_data[2]=int(input())
Print("[bold][green] enter the user weight")
user_data[3]=int(input())
Print("[bold][green] enter the user hight")
user_data[4]=int(input())

```

#Sedentary (little to no exercise): TDEE x 1.2-----1

#Lightly active (light exercise/sports 1-3 days/week): TDEE x 1.375-----2

#Moderately active (moderate exercise/sports 3-5 days/week): TDEE x 1.55-----3

#Very active (hard exercise/sports 6-7 days a week): TDEE x 1.725-----4

#Extra active (very hard exercise/sports & physical job or 2x training): TDEE x 1.9-----5

```
Print("[bold][blue]1:", "[bold][red] Sedentary (little to no exercise)")
Print("[bold][blue]2:", "[bold][red] Lightly active (light exercise/sports 1-3 days/week)")
Print("[bold][blue]3:", "[bold][red] Moderately active (moderate exercise/sports 3-5 days/week)")
Print("[bold][blue]4:", "[bold][red] Very active (hard exercise/sports 6-7 days a week)")
Print("[bold][blue]5:", "[bold][red] Extra active (very hard exercise/sports & physical job or 2x
training)")

Print("[bold][green] enter the user activity level based on above")
user_data[5]=int(input())
required=required_cal(user_data)
#print(user_data)
nutrients_c= ['Calories', 'Total Fat(g)', 'Saturated Fat(g)', 'Polyunsaturated Fat(g)',
              'Monounsaturated Fat(g)', 'Cholesterol(mg)', 'Sodium(mg)',
              'Total Carbohydrates(g)', 'Dietary Fiber(g)', 'Sugars(g)',
              'Protein(g)', 'Calcium(mg)', 'Iron(mg)', 'Potassium(mg)']

print('\n\n')
Print(f"[bold][purple]The below data contains the required amount of nutrition based on user data")
for i in range(14):
    Print(f"[bold][red]{{nutrients_c[i]}}:", f"[bold][green]{{required[0][i]}}")
print(user_intake.reshape(15)[1:], '\n\n', required[0])
print('\n\n')
plot(user_intake.reshape(15)[1:], required[0])
```