Meal Recommender system

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Meal Recommender System

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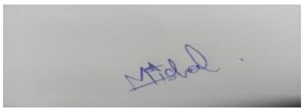

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Dedication

This thesis is dedicated to all working mothers who leave their children in daycare centers and are concerned about children's health and wellbeing.

Acknowledgments

Glory be to Allah (S.W.A), the Creator, the Sustainer of the Universe. Who only has the power to honour whom He please, and to abase whom He please. Verily no one can do anything without His will. From the day, I came to NUST till the day of my departure, He was the only one Who blessed me and opened ways for me, and showed me the path of success. Their is nothing which can payback for His bounties throughout my research period to complete it successfully.

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Abstract

Working mothers entrust their children to daycare centers, which in turn provide parents with a detailed report of the food given to the child throughout the day. This research work develops an application that uses the image of a nutrient to calculate its caloric value. It assists the parents to make sure that their child is consuming the right amount of nutrition. Taking the right amount of nutrition is necessary for the development of a child, as every nutrition plays a significant role in growth. For this purpose a Meal Recommendation System is designed, This system takes the uploaded image by the user as an input and recognizes the food. For the food recognition, different models like CNN, Inception V3, MobileNet, yolov5, and yolov8 are trained on FOODD, ECUSTED, and Food-360 datasets. From the findings of the research work it is revealed that yolov8 comparatively gives better results than other models. The area of the image is calculated using image segmentation and then micro-nutrient values of the recognized food are calculated from openfoodfacts dataset. These recognized foods along with mass and micro-nutrient values are saved in the food log. From the food log, we calculate the total intake of the child, and from the age group we find the required nutrient values given by dietician and by subtracting total intake from requirements deficiencies are calculated. Consequently, The deficiencies are calculated and data from the openfoodfacts helps to recommend the foods that are high in those nutrient values in deficiencies. Hence, the appropriate food is recommended. The recommended food is validated by looking at the values which they highly contained.

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LIST OF SYMBOLS, ABBREVIATIONS AND ACRONYMS

Abbreviations

Abbreviation	**Definition**
NUST	National University of Sciences and Technology
SEECS	School of Electrical Engineering and Computer Sciences
DoC	Department of Computing
AI	Artificial Intelligence
CNN	Convolutional Neural Network
CSV	Comma-Separated Values
DB	Database
GAN	Generative Adversarial Network
YOLO	you only look once
ML	Machine Learning
UI	User Interface
API	Application Programming Interface
μg	Microgram
g	Gram
kg	Kilogram
mL	Milliliter
kcal	Kilocalorie
mg	Milligram
cm	Centimeter
mm	Millimeter

Abbreviation	**Definition**
mm^2	Square Millimeter
mm^3	Cubic Millimeter
N	Nutrient
ΔN	Nutrient Deficiency
R	Recommended
T	Timestamp
I	Image
M	Mass
V	Volume

CHAPTER 1

Chapter 1 : Introduction

A Safe and supervised environment is provided in daycare centers for children. While parents are busy with jobs and other responsibilities, they have peace of mind knowing that their children are well cared for. To maintain the proper growth of the body, children require a high amount of calories during the growth period.

1.1 Problem Statement

Children's daycare centers play a crucial role in providing a secure and supervised environment for young children, allowing parents to manage their hectic schedules and various obligations with peace of mind. These centers are not just custodial spaces; they are pivotal in ensuring the holistic development of children, particularly in terms of their nutritional needs. The early years of a child's life are marked by rapid growth and development, necessitating a balanced and adequate intake of calories and nutrients to support this critical phase. Proper nutrition during this period is essential for maintaining healthy body growth, cognitive development, and overall well-being.

1.2 Motivation

For a secure and caring environment during the day, daycare centers are a source of great comfort for many working mothers. In order to guarantee that the children's nutritional needs are satisfied, these centers usually provide a list of the foods the kids have eaten. However, this information is frequently inaccurate. The application that this research develops will help parents make sure their child is getting the right amount of nutrition by using pictures of food to calculate calorie and nutrient values. Utilizing an uploaded image as input, the Meal Recommender System is built to identify food and offer nutritional information. Along with providing individualized recommendations to address any nutritional deficiencies, this approach assists in monitoring the child's diet.

1.3 Research Objectives

1. **Choosing the best dataset for the recommender system:** Determine and make use of the best dataset for precise food identification and nutrient estimation.
2. **Image recognition to recognize the food on the plate:** Create and apply techniques to reliably identify different food items from images in order to identify the food on the plate.
3. **Image segmentation to get the quantity of food:** Utilize image segmentation techniques to ascertain the mass (quantity) of the identified food items that have been identified.
4. **Maintaining the nutritional values in a food log:** Effectively record and handle the dietary data of the recognized food items. Nutrient values are counted in order to determine the user's daily nutrient intake. This is done by using food consumption data that has been logged.
5. **Recommending food based on the deficiencies of the child:** Food recommendations based on the child's deficiencies: Determine the child's nutrient deficiencies and suggest foods to make up for them.

1.4 Research Gap:

Meal recommender system systems currently in use have a number of drawbacks. In order to fill in these gaps, the following areas will be the main emphasis of this study:

1. **Accuracy of image segmentation techniques:**Assessing the efficiency of techniques for identifying nutrient values from meal images.
2. **Efficient algorithm development:**Creating an effective algorithm to make meal recommendations based on the determined nutrient values.

3. **Performance evaluation:** Monitoring the meal recommender system's effectiveness to make sure the suggested meals are nutrient-balanced.

1.5 Research Questions

The study tackles a number of important issues, including:

1. **Dataset suitability:**Which dataset is best suited for a meal recommender system?
2. **Food recognition:** How can different food items be recognised from user-uploaded images with accuracy?
3. **Food quantity determination:**How can the quantity (mass) of food items be calculated using image segmentation?
4. **Nutritional information management:**How can nutritional information be logged and managed effectively?
5. **Daily nutrient intake calculation:** How can the daily nutrient intake be calculated using logged food consumption data?
6. **Nutrient deficiency identification:** How can nutrient deficiencies be identified and addressed through recommended foods?

1.6 Importance of Proper Nutrition in Early Childhood

Childcare facilities are essential in giving young children a safe and supervised environment so that parents can handle their busy schedules and other responsibilities with peace of mind. These facilities serve more purposes than just child care; they are essential to a child's overall development, especially in terms of their nutritional requirements. Early childhood is a time of rapid growth and development in children, so it's important to provide them with a balanced and sufficient intake of calories and nutrients to support this important stage of life. Maintaining healthy body growth, cognitive development, and general wellbeing during this time requires proper nutrition.

CHAPTER 2

Chapter 2: Literature Review

The rise in nutritional disorders such as diabetes, obesity, and heart disease brought on by unhealthy eating patterns has brought attention to the critical need for efficient diet management programs in recent years. Continuous dietary monitoring is hampered by existing methods, which frequently rely on manual input through smartphone apps like MyFitnessPal and lack real-time food attribute estimation. The suggested system incorporates cutting-edge deep learning methods to get around these restrictions. It uses transfer learning and data augmentation to improve model robustness against variations. It uses Convolutional Neural Networks (CNNs), namely Inception-v3 and Inception-v4 models, for accurate food recognition from images. In order to estimate the nutritional content and ingredients of recognized food items, the system also includes an attribute estimation module that uses a vector space model with Word2Vec embeddings. Findings show notable improvements in performance, with the Inception-v4 model outperforming benchmarks and reaching an 85 percent top-1 accuracy on a variety of datasets. Prospective avenues for development encompass optimizing the usability of the mobile application "Rate Your Plate," augmenting the dataset to enhance precision, enhancing attribute estimation via sophisticated natural language processing, and verifying the system in healthcare environments via comprehensive user testing. Overall, this system is a ground-breaking development in mobile-based dietary assessment that offers accurate, automated, and user-friendly solutions for impact.[10]

In recent years, rising dietary ailments like obesity, diabetes, and heart diseases stemming from unhealthy eating habits have underscored the critical need for effective diet management systems. Current methods, reliant on manual input through apps like MyFitnessPal and SHealth, often lack real-time food attribute estimation, impeding continuous dietary monitoring. To address these gaps, the proposed system integrates advanced deep learning techniques. It employs Convolutional Neural Networks (CNNs), specifically Inception-v3 and Inception-v4 models, for precise food recognition from images, bolstered by transfer learning and extensive data augmentation to enhance model resilience to variations. The system also includes an attribute estimation module utilizing vector space models with Word2Vec embeddings to gauge nutritional content and ingredients of identified food items. Results highlight the Inception-v4 model achieving an 85% top-1 accuracy on a diverse dataset, surpassing benchmarks. Future enhancements include refining the "Rate Your Plate" mobile app, expanding and diversifying the dataset, advancing attribute estimation through natural language processing, and validating the system in healthcare settings. In summary, this system represents a pioneering stride in mobile-based dietary assessment, offering an automated, precise, and user-friendly solution for effective diet management and health improvement. [14]

Automated food recommender systems, which attempt to match meals with nutritional objectives and individual preferences, are providing more and more support for diet management—a critical component of controlling chronic diseases like diabetes. Incomplete user food preference data is a common cause of current system failure. Conventional techniques, such as collaborative filtering (CF) and content-based filtering (CB), recommend items based on similar item attributes or user preferences, but their efficacy and availability may be constrained. Though they aim to increase accuracy, recent innovations still heavily rely on detailed user data from recipe rating sites or user submissions. Examples of these innovations include incorporating ingredient details into collaborative filtering algorithms or predicting user ratings based on ingredient liking. Accurately recording food consumption frequency—which is essential for accurate preference prediction—is one of the challenges. While convolutional neural networks (CNNs) can be used to learn preferences from food images, alternative methods use food logs to infer preferences based on usage frequency. However, image-based methods might not be feasible for home meal preparation. [12]

While querying knowledge graphs for food recommendations aims to match food logs or favorite foods with suitable recipes or pairings, integrating food preferences into menus and making adjustments based on user feedback offers an additional approach. There are still issues with inconsistent food naming and structure across platforms, even with advancements in food logging apps like MyFitnessPal and Cronometer. In order to overcome these difficulties, this paper suggests a word embedding approach that processes food logs from Cronometer and the USDA's FNDDS database in order to identify preferences and label food entries using Word2Vec embeddings and k-Nearest Neighbors Classification. Although the evaluation produced encouraging results, handling non-Western foods and dataset size need to be improved. Future improvements include adding TF-IDF weighting for word importance, integrating advanced embeddings like BERT or ELMo for better context, and including a recommendation component for healthier food variants catered to metabolic goals. Real user evaluations are planned to further improve the methodology. This review highlights the potential of embedding-based methods in identifying personalized food preferences for improved dietary management tools, while also highlighting the ongoing challenges and advancements in the development of accurate food recommender systems. [4]

By anticipating user preferences, recommender systems (RS) improve the effectiveness and satisfaction of decision-making. There are several approaches and limitations associated with traditional recommendation systems (RS), such as Collaborative Filtering (CF), Content-Based Filtering (CB), and Hybrid Recommendation algorithms. CF systems use past user data, such as purchases and ratings, to generate recommendations. These systems include neighborhood-based (user-based and item-based) and model-based approaches, such as Latent Factor Models. Conversely, CB systems use other item attributes to suggest items that are comparable to the ones the user has already liked. In order to increase recommendation accuracy, hybrid algorithms combine the advantages of both the CF and CB techniques. [13].

The recommendations made by Health Recommender Systems (HRS), a type of specialized recommendation system (RS) designed for the healthcare industry, must meet certain health standards and frequently deviate from user preferences. Mandatory feature (MF) requirements are imperative for healthcare scenarios such as dietary management, and the MATURE model tackles these issues by incorporating them into recommendation processes. MATURE guarantees that recommended items satisfy both mandatory nutritional needs and user preferences by utilizing cosine similarity measures and feature-based classification. Analysis in multiple scenarios shows that MATURE is more effective than traditional RS models, which give priority to user preferences over important health criteria, in terms of continuously meeting required requirements. [7]

In contrast to conventional approaches that concentrate on dish classification and recipe generation, food image segmentation is essential for health applications like calorie and nutrient estimation. The segmentation model's performance is hampered by the absence of fine-grained ingredient labels and masks in existing datasets. This is fixed by FoodSeg103 and its extension, FoodSeg154, which use pixel-wise masks to combine 9,490 images with 154 ingredient classes. ReLeM improves segmentation by combining visual data and recipe language embeddings, increasing recognition accuracy in models such as FPN, SeTR, and CCNet. The effectiveness of ReLeM is demonstrated by the results on FoodSeg103 in terms of mean accuracy (mAcc) and mean intersection over union (mIoU). Cross-domain experiments on Asian cuisines con- firm the coherence of ReLeM. In order to improve food image segmentation for better dietary management, future work will try to increase datasets, improve annotations, optimize ReLeM, investigate new models, and apply findings to useful health tools. [6]

By automating food recognition and portion size estimation using cutting-edge deep learning techniques, the "End-to-End Food Image Analysis System" marks a substantial advancement in dietary assessment. In the past, dietary assessment was done manually, which was labor-intensive and error-prone. Using RGB images and energy distribution maps from a conditional GAN, this system enhances portion size estimation for food localization and classification by integrating Faster R-CNN with ResNet-50. Through data augmentation methods like flipping and rotation, it strengthens the model's resilience in the face of sparse training data. Tested on a dataset comprising 154 photos of eating occasions and 915 food items in 31 categories, the system outperforms current methods in portion size estimation with a Mean Absolute Error (MAE) of 105.64 Kcal, and at an IoU threshold of 0.5, it achieves a mean average precision (mAP) of 0.6235. Expanding the diversity of datasets, investigating sophisticated architectures such as attention mechanisms, and integrating with other modalities for comprehensive dietary assessment tools in clinical and research applications are some of the future work that will be done with the goal of improving health outcomes through accurate dietary analysis. [5]

The paper "Deep Learning-Based Food Calorie Estimation Method in Dietary Assessment" tackles the significant problem of precise dietary assessment in the fight against obesity, which carries significant health risks such as type 2 diabetes and cardiovascular diseases. Because they rely on user memory, traditional methods like food diaries and 24-hour recalls are prone to errors. This study promotes computer vision as a viable remedy, automating the analysis of food images to estimate calories. The technique makes use of GrabCut for precise image segmentation, Faster R-CNN for accurate food and object detection, and volume estimation methods customized for different food shapes. With Faster R-CNN achieving 93.0 percent mean Average Precision in food detection and promising accuracy in volume and mass estimation, the results show robust performance. In order to improve obesity management and related health outcomes, future research will focus on improving algorithm accuracy across a variety of food types, optimizing for real-time applications, expanding dataset diversity, and developing user-friendly interfaces for practical integration into health monitoring systems. [2]

The article "An Automated Image-Based Dietary Assessment System for Mediterranean Foods" discusses the pressing need for cutting-edge instruments to control dietary intake in light of the rise in diseases like diabetes, obesity, and cardiovascular disorders. It highlights how deep learning, computer vision, and AI are revolutionizing dietary assessment. The study improves food classification and volume estimation accuracy by introducing the MedGRFood dataset, which is specifically designed for Mediterranean cuisine. The system outperforms conventional techniques that rely on generic datasets like ImageNet, achieving remarkable classification accuracies of 83.8% top-1 and 97.6% top-5 using the EfficientNetB2 model that has been pre-trained on food-specific data. Using stereo vision techniques, the volume estimation subsystem performs robustly in quantifying food volumes, achieving a mean absolute percentage error (MAPE) of 10.5 percent across 148 dishes. In order to support proactive management of diet-related health issues globally, future work will involve expanding the dataset, optimizing model performance, integrating the system into mobile applications for real-time dietary monitoring, and advancing nutrient analysis capabilities. The study "Measuring Calorie and Nutrition From Food Image" examines key ideas and methods for measuring calories and nutrients from food images. [3]

Using image-based food recording to encourage healthier eating habits, the study examines important theories and methods in food recognition and nutrition estimation. In contrast to laborious manual procedures, it emphasizes the practicality of smartphone and wearable image sensors for this purpose. Food image processing and segmentation techniques include saliency detection and hierarchical segmentation. A multiple class SVM is trained for food item classification using low-level features extracted by feature extraction techniques such as Dense HOG and Dense SIFT. With feature fusion, the system performs better, achieving over 85% accuracy in identifying 15 different food categories. Subsequent research endeavors to customize the system according to user preferences and geographical location, broaden the food ontology, enhance portion size estimation through the utilization of depth images, and carry out comprehensive real-world trials to verify and improve system functionality in various scenarios. [9]

The study emphasizes how crucial it is to monitor calorie intake in order to maintain a healthy diet, as well as the value of fruit recognition in agriculture for tasks like yield prediction and disease detection. It examines developments in deep learning, specifically with regard to Convolutional Neural Networks (CNNs), which have outperformed conventional techniques in tasks involving object classification. For fruit recognition and calorie estimation, methods include utilizing a customized five-layer CNN architecture and pre-trained models (VGG-16, DenseNet-121, InceptionV3). In order to prepare the data for training, images from IEEE dataport and Kaggle were resized to 512x512 and 256x256 pixels. Findings show that the five-layer CNN attained high accuracy rates: testing at 99.45 percent, validation at 95.30 percent, and train- ing at 99.60 percent. Upcoming projects include refining model training on bigger datasets, investigating advanced cloud platform deployment, integrating with IoT devices for real-time applications, and creating more approachable user interfaces for wider accessibility. [11]

The study emphasizes how crucial it is to track caloric intake for weight control and overall health, especially in the fight against obesity, which is defined as having a BMI of 30 or higher. It promotes automated systems by highlighting the drawbacks of conventional manual calorie estimation techniques. The model performs exceptionally well in food item identification thanks to the use of Convolutional Neural Networks (CNNs) and TensorFlow's object detection API. Important methods include volume estimation with K-Mean clustering, GrabCut for segmentation, and Faster RCNN for object detection. While calorie estimation accuracy varies, the results demonstrate significant improvements in food classification accuracy (97 percent) and decreased volume estimation errors (mean 21 point 06 percent). The article discusses how important it is to classify foods accurately and estimate their attributes in order to encourage a healthy diet and fight obesity. It focuses on automating food image classification and attribute estimation using machine learning, more especially convolutional neural networks (CNNs), giving users real-time information to make educated food choices. The key strategies are data augmenta- tion to improve model robustness, text data retrieval for attribute estimation using Word2Vec embeddings, and transfer learning with Inception-v3 and Inception-v4 CNN models tuned on a varied dataset. The system's effectiveness in real-time scenarios is validated by the experimental results, which demonstrate high classification accuracy (91.73 percent with Inception model) and successful attribute estimation. In order to facilitate a wider rollout of the system across mobile and web platforms, future research will concentrate on refining the recognition of complex foods, growing datasets, improving nutritional analysis capabilities, and optimizing system usability. [8]

The goal of the paper "goFOODTM: An Artificial Intelligence System for Dietary Assessment" is to estimate the nutritional content of meals using images taken with smartphones. It addresses issues with existing approaches, emphasizes the significance of precise dietary assessment for health management, and talks about developments in artificial intelligence and computer vision for automating dietary analysis. Among the fundamental methods are IMU data for camera pose optimization, deep neural networks for food detection and segmentation, and 3D reconstruction for volume estimation. The results, which were verified against evaluations from dietitians, demonstrate high accuracy in food segmentation (94 point 4 percent F-score) and enhanced nutrient estimation over conventional methods. In order to support more research in dietary assessment and AI applications, future work will try to improve accuracy and usability, broaden platform availability, and encourage data sharing. [1]

In the paper "A Comprehensive Survey of Image-Based Food Recognition and Volume Estimation Methods for Dietary Assessment," obesity and cardiovascular disorders are among the health issues linked to unhealthful eating practices. It criticizes the low adherence and inaccuracies of traditional manual food logging and argues in favor of machine learning techniques for automated dietary assessment through smartphone apps. The use of CNNs in particular for deep learning is crucial for precise volume estimation and food identification. The survey's findings, which cite high accuracy rates on benchmark datasets like UECFOOD-256 and Food-101, demonstrate CNNs' superiority over conventional techniques in the recognition of food images. In order to improve food recognition reliability and usability, future research aims to diversify datasets, address model biases, improve continual learning, and enhance transparency in AI systems. [15]

The World Health Organization has highlighted the importance of obesity and overweight in relation to global health. The paper "CALORIE MEASUREMENT AND CLASSIFICATION OF FRUITS USING IMAGE PROCESSING: A REVIEW" addresses these issues and looks at creative approaches to measuring calories, especially using image-based fruit recognition systems. It compares and contrasts contemporary strategies like electronic dietary assessment and advanced image processing techniques with more established ones like DLW and 24-hour dietary recall. These include the following: pre-processing steps such as noise reduction and histogram equalization; segmentation using thresholding and morphological operations; feature extraction involving color histograms and texture descriptors; and classification using SVM, NN, and Bayesian methods. Image acquisition with calibration cards for accurate representation is one of these. When these methods are combined, fruit classification tasks can achieve high accuracy rates of up to 99 percent. However, consistent segmentation still presents challenges, particularly for fruits with irregular shapes or textures. Future work will focus on improving segmentation algorithms, investigating sophisticated feature extraction, utilizing AI for automation, and creating useful, approachable systems for widespread use in calorie estimation and diet monitoring. [**b16**]

T he development of meal recommendation systems and dietary assessment tools has garnered significant attention in recent years, as researchers aim to leverage technology to address various nutritional challenges. A comprehensive review of existing literature reveals a multitude of approaches and methodologies employed to enhance the accuracy and efficacy of these systems.

References	Background theories	Core techniques	Results	Future work
Yunus, R., Arif, O., Afzal, H., Amjad, M. F., Abbas, H., Bokhari, H. N., Haider, S. T., Zafar, N., Nawaz, R. (Year). A Framework to Estimate the Nutritional Value of Food in Real Time Using Deep Learning Techniques. 2019.	Rapid increase in dietary ailments caused by unhealthy food routines. Importance of dietary assessment systems for improving dietary habits and promoting healthy life.	Deep learning models for food identification. Fine-tuned Inception model for recognizing food items. Data augmentation, multicrop evaluation, regularization techniques	Achieved 85% classification accuracy on a dataset with 100 classes and an average of 1000 images per class. Efficient performance on both the basic Food-101 dataset and its extension for sub-continental foods.	Practical application of the proposed system. Improvements in the mobile app with advanced features to serve as a comprehensive guide for everyday meals.

M. Gawande, "Fruit Image Recognition and Calorie Measurement Using Convolutional Neural Network (CNN)," May-June 2021.	Deep Learning and Image Recognition Health and Wellness	Convolutional Neural Networks (CNNs) Tensor Flow Lite and Teachable Machine	A user-friendly web-based application was developed to capture images, recognize fruit, and automatically calculate calories	Future work may involve expanding the dataset to include more fruit types and improving the model's robustness. -Additional features could be integrated into the application, such as real-time recognition and user feedback mechanisms
Ahmed A. Metwally1,2, , Ariel K. Leong3, , Aman Desai4 , Anvith Nagarjuna1 , Dalia Perel- man1 , Michael Snyder1, 2021, Learning Personal Food Preferences via Food Logs Embedding	• CF • CB • Knowledge graph	• Clustering (K-Means) • word2vec • Cosine similarity	The method generates and compares word embeddings to identify the parent food category of each food entry and then calculates the most popular. It identifies 82% of a user's ten most frequently eaten foods.	To add a Recommender component to our food preference learning system. After learning the kinds of foods, the user prefers to eat, the system will use nutritional information to recommend healthy variants of the favored foods that fit with the user's metabolic goals

Ritu Shandilya, Sugam Sharma, Johnny Wong ,2022, MATURE-Food: Food Recommender System for MAndatory FeaTURE Choices A system for enabling Digital Health	• Recommender system • Collaborative Filtering (CF) • Content-Based Filtering (CB) • Deep learning	• Feature-Based Classification of Items • Computing features of each Class (CxF) • Computing Mandatory Features (MF)	MATURE, considers, assures, and accommodates the MFs requirements in its entirety throughout all the recommended items with accommodation of past preferences as much as possible.	we further developed MATURE, which made the content-based Recommender
Xiongwei Wu, Xin Fu, Ying Liu, Ee-Peng Lim, Steven C.H. Hoi, Qianru Sun, 2021, A Large-Scale Benchmark for Food Image Segmentation	• GAN • Faster RCNN with VGG and ResNET • Pytorch • RESNET-50	• Data augmentation • Food Localization and Classification • RGB distribution image	It proposes an end-to-end image-based food analysis framework that integrates food localization, classification and portion size estimation.	

Yanchao Lianga, , Jianhua Li, 2018, Deep Learning-Based Food Calorie Estimation Method in Dietary Assessment	• Faster RCNN • GrabCut • SVM	• Image acquisition • Object detection • Image segmentation • Volume estimation • Calorie estimation	The volume is estimated with volume estimation formulas. It estimate each food's calorie	The estimated calories can be used to further recommend food
Fotios S. Konstantakopoulos, Eleni I. Georga, and Dimitrios I. Fotiadis, Fellow, IEEE,2023, An Automated Image-Based Dietary Assessment System for Mediterranean Foods	• MedGRFood dataset • CNNs	• MedGRFood Image Dataset • Food Classification Subsystem • EfficientNet • Transfer Learning and Fine-tuning	The proposed automated image-based dietary assessment system provides the capability of continuous recording of health data in real time.	A limitation of the proposed methodology is that it estimates the nutritional composition of foods contained only in shallow dishes which must be improved to include different types of dishes

P. Pouladzadeh, S. Shirmohammadi, and R. Al-Maghrabi, "Measuring calorie and nutrition from food image," IEEE Trans. Instrum. Meas., vol. 63, no. 8, pp. 1947, Aug. 2014.	• Image Processing and Segmentation • Nutritional Fact Tables	• Support Vector Machine (SVM) • Mobile Device Integration	The system demonstrated acceptable accuracy in measuring food portion areas, volumes, and subsequent calorie content. The method effectively supports both dieticians and individuals in managing daily food intake and controlling weight.	Expand coverage to include a wider variety of food types from different global cuisines. Enhance the system to accurately measure mixed or liquid foods.
W. Zhang, Q. Yu, B. Siddiquie, A. Divakaran, and H. Sawhney, "Snap-n-Eat: Food recognition and nutrition estimation on a smartphone," J. Diabetes Sci. Technol., vol. 9, no. 3, pp. 525-533, May 2015.	• Hierarchical Segmentation • Feature Extraction and Classification	• Linear Support Vector Machine (SVM) • Mobile and Web Integration	Achieved over 85% accuracy in detecting 15 different kinds of food items in images taken in real-life settings with cluttered backgrounds. The system effectively automates the process of food recognition and nutrition estimation without requiring user intervention.	Enhance the system to personalize the food recognition classifier based on user habits, location, and other metadata. Improve the system's capability to handle a broader range of food items and more complex scenarios.

V. K. Roy, G. K. Roy, V. Thakur, N. Baliyan, N. Goyal, and Y. Chauhan, "Real-time fruit recognition and calories estimation using CNN and model deployment on Amazon's AWS," in Proc. 2021 IEEE International Conference on Computer Vision and Pattern Recognition (CVPR), Virtual Event, 2021, pp. 1-6.	• Deep Learning for Agricultural Use • Data Labeling	• Customized CNN and Pre-trained Models • AWS Deployment	Achieved a highest accuracy of 99.60% in fruit recognition using the customized five-layer CNN. -Successfully tested on real-time fruit images with an accuracy of 99.45%, demonstrating practical application and effectiveness.	Extend the system to support broader dietary and health applications, aiding users in computing food consumption and gathering dietary details. -Improve and expand the model to cover more fruit types and potentially other food items for a comprehensive dietary management tool.

V. B. Kasyap and N. Jayapandian, "Food calorie estimation using convolutional neural network," in 2021 3rd International Conference on Signal Processing and Communication (ICPSC), Coimbatore, India, 13-14 May 2021.	• Body Mass Index (BMI) and Calorie Monitoring • Deep Learning for Calorie Estimation	• Convolutional Neural Network (CNN) • Complementar Algorithms	The CNN model showed improved accuracy with a reduction in volume error estimation by 20%. -Random Forest model outperformed the K-Nearest Neighbors (KNN) model in volume estimation, with a mean error of 13.12 compared to KNN's 21.06.	Expand the dataset to reduce errors and enhance model accuracy further. -Address imbalanced data distribution in the dataset to minimize errors and improve model performance.

Z. Shen, A. Shehzad, S. Chen, H. Sun, and J. Liu, "Machine learning based approach on food recognition and nutrition estimation," in 2019 International Conference on Identification, Information and Knowledge in the Internet of Things (IIKI2019), Wuhan, China, 2019, pp. 1-6	• Dietary Assessment and Nutritional Information • Artificial Intelligence for Food Analysis	• Deep Neural Networks • 3D Reconstruction Algorithm • Nutrient Database Integration	goFOODTM outperformed experienced dietitians in estimating calories and macronutrients for normal central-European meals and showed comparable performance for fast food standardized meals. -The system achieved a top-3 accuracy of 71.8%. for fine-grained food categories	Continuous development to improve accuracy, speed, user-friendliness, and integration of new features like a bar-code scanner for packaged foods. -Utilizing the simplified goFOODTM-Lite version for retrospective dietary tracking and large-scale research projects in both technical and nutritional fields

G. A. Tahir and C. K. Loo, "A comprehensive survey of image-based food recognition and volume estimation methods for dietary assessment," Healthcare, vol. 9, no. 12, article 1676, Dec. 2021. [Online]. Available: https://doi.org/10.3390/healthcare9121676	• Dietary Problems and Chronic Diseases • Machine Learning in Dietary Monitoring	• Visual-Based Methods and CNNs • Food Image Databases	Around 66.7% of studies use CNNs for food recognition, and 46.2% of mobile applications implement CNNs, demonstrating their effectiveness in ingredient detection. -34.5% of techniques require multiple images for volume estimation, while the rest use single images, with multi-view methods being more accurate but complex.	Need for larger, more diverse food image datasets and methods capable of open-ended continuous learning to avoid catastrophic forgetting. -Explore unsupervised methods like contrastive learning and improve model transparency using explainable AI to enhance food recognition and dietary assessment.

M. Basantsingh Sardar, "Calorie measurement and classification of fruits using image processing: A review," Int. J. Res. Eng. Technol., vol. 5, no. 5, pp. 364, May 2016.	• Obesity and Public Health • Technology for Dietary Awareness	• Image-Based Systems • Fruit Segmentation and Recognition	All approaches follow a systematic framework involving pre-processing and post-processing, focusing on accurate object classification and segmentation.	Future work involves improving existing systems with optimized software and enhancing user-friendliness. -Utilizing MATLAB for image processing can help create accurate and cost-effective systems.

Table 2.1: Literature Review

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CHAPTER 3

Chapter 3: Proposed Methodology

In this section, we described the modules of the proposed system. The whole system is comprised of the following modules:

- Image recognition module.
- Image segmentation module
- Database module
- Recommendation module

3.1 Dataset

The goal of this study is to create a comprehensive dataset of foods that are suitable for children and are easily accessible across the subcontinent. The basis for creating a strong meal recommendation system that is suited to the dietary requirements of kids in daycare facilities will be provided by this dataset. The best publicly available datasets were chosen after a thorough review and analysis of a large number of food datasets was carried out in order to accomplish this goal. Because of their rich content and alignment with the project's goals, Fruit-360, FOODD, and ECUSTFD stood out as the top picks among the reviewed datasets.

3.1.1 Fruit-360:

One of the most well-known and frequently used datasets in the field of food image recognition is Fruit-360. It is made up of an enormous number of photos of fruits and vegetables arranged into 131 different categories. Creating a thorough meal recommender system requires a wide representation of different fruit and vegetable types, which is ensured by this thorough categorization. In order to facilitate model training and evaluation, the dataset comprises 90,483 images in total that have been carefully separated into training and test sets.

Training Set: The dataset for training consists of 67,692 images with a resolution of 100 by 100 pixels each. These images are utilized as the main source of data to train the machine learning models. The resolution of each image allows for precise classification while still keeping the dataset at a manageable size for efficient processing.

Test Set: There are a total of 22,688 images in the test set, which are utilized to assess the effectiveness and ability to generalize of the trained models. The uniform image resolution throughout the dataset is essential for developing strong and reliable models.

The Fruit-360 dataset's extensive coverage and excellent image quality make it a priceless tool for this study, offering a strong basis for refining and evaluating the meal recommender system's fruit and vegetable identification capabilities.

3.1.2 FOODD Dataset:

Another important resource for this study is the FOODD dataset, which was created especially for tasks involving the detection of food. It has three thousand photos in all, covering a variety of food items in different settings. The dataset is more useful for creating dependable and accurate food recognition models because of its thoughtful design.

Image Diversity: Photos of food taken under different lighting conditions and with different cameras are included in the FOODD dataset. In order to ensure that the meal recommender system can reliably identify food items in daycare settings regardless of the lighting or camera used, this diversity is essential for building models that are resilient to variations in real-world scenarios.

Background Consistency: Food items are displayed on white plates in every image in the FOODD dataset, with the background being ignored. Because of this consistency, background noise is reduced during image processing, making it easier for the models to concentrate only on the food items.

Calibration Tool: The use of a thumb in the images serves as a calibration tool to measure the real sizes of the food items. This unique method offers a point of reference for accurately estimating size, which is essential for determining portion sizes and, in turn, the nutritional value of the meals. The meticulous attention to detail and practical features of the FOODD dataset make it a valuable resource for improving the food detection capabilities of the meal recommender system.

3.1.3 ECUSTFD Dataset:

The ECUSTFD dataset adds a distinct viewpoint by including pictures of food items taken from both the top and side, adding a variety of visual details to the dataset. This collection of 2,978 photos, which depict 19 distinct food kinds, is an important contribution to the field of study.

Multi-View Representation: The ECUSTFD dataset offers thorough visual data by capturing food items from various perspectives, which can raise the precision of food recognition models. The models' robustness and reliability are increased by this multi-view approach, which enables them to learn distinguishing features from various angles.

Calibration Object: A Yuan coin is used by the dataset as its calibration object, which guarantees uniform size references throughout the pictures. The accuracy of nutritional assessments is directly impacted by this feature, which is essential for precise volume and size estimation.

Additional Information: The ECUSTFD dataset provides detailed textual data for each training image, such as annotations, mass, volume, density, and energy content. This additional information is essential for creating models that can not only identify food items but also accurately predict their nutritional values.

The extensive and detailed dataset from ECUSTFD is crucial to this research, playing a significant role in the advancement of a meal recommender system that can provide accurate and dependable dietary evaluations.

Thoroughly compiling and analyzing datasets like Fruit-360, FOODD, and ECUSTFD forms a strong basis for crafting a specialized meal recommendation system for kids in daycare. Using the vast array of visual and written data in these sources, the goal is to build a complete tool that streamlines the process of monitoring and supporting children's dietary requirements, leading to better overall growth and well-being.

3.2 Image recognition module

The initial and crucial stage in the proposed pipeline is identifying fruits. An precise recognition of fruits sets the groundwork for the following steps in the meal recommendation system. Multiple models for recognizing fruits have been created and tested, with the decision based on their performance measures such as precision, efficiency, and durability. This part offers a comprehensive analysis of the methods used, explaining the structure and training procedure of each model.

3.2.1 CNN:

The fruit recognition model initially used is a classic Convolutional Neural Network (CNN). CNNs are recognized for their capability to understand spatial patterns in images via convolutional layers. The CNN model was trained on the FOODD dataset, initially with 7 classes and later increased to 15 classes. The CNN model consists of five convolutional layers, each accompanied by dropout layers to avoid overfitting, and activation functions such as ReLU (Rectified Linear Unit) to introduce non-linearities.

Architecture Details: Convolutional Layers: The model consists of five convolutional layers, each specifically crafted to extract various levels of features from the input images. These layers utilize filters for convolution operations, followed by pooling layers to decrease spatial dimensions and computational burden.

Dropout Layers: After every convolutional layer, dropout is utilized to prevent overfitting by randomly deactivating a portion of the input units during training. This helps prevent the model from becoming overly dependent on any individual feature and allows for better generalization to unseen data.

Activation Functions: The purpose of ReLU activation functions is to introduce non-linearity, allowing the model to effectively capture intricate patterns within the data.

Output Layer: The last layer is a softmax layer that produces the probability distribution among the classes.

Loss Function: The categorical cross-entropy loss function is employed to assess the difference between the predicted and actual class distributions.

Optimizer: During training, the Adam optimizer is used to minimize the loss function and adjust the network's weights. It combines the benefits of AdaGrad and RMSProp, two other extensions of stochastic gradient descent.

3.2.2 Inception V3:

The Inception V3 model is recognized for its superior efficiency and accuracy in deep learning. It utilizes various architectural advancements such as factorized convolutions and robust regularization to enhance its performance. In this study, the Inception V3 model was trained using 36 classes from the Fruit-360 dataset.

Architecture Details:

Pre-trained Model: We obtained the Inception V3 model from the ImageNet dataset, which already has pre-trained weights. By utilizing transfer learning, we took advantage of the pre-trained model's general feature recognition capabilities and fine-tuned it for the specialized task of fruit recognition.

Global Average Pooling 2D Layer: Through the feature map averaging process, this layer takes the place of the fully connected layers, lowering the possibility of overfitting.

Fully Connected Layer: To ensure that the model can effectively generalize to new data, a dense layer with dropout is added for classification.

Training Details:

Customization: To enable fine-tuning, the pre-trained model's upper classification layers were eliminated. A dense layer with ReLU activation, a GlobalAveragePooling2D layer, and a final softmax layer for classification were added. **Data Augmentation:** To boost the diversity of the dataset and strengthen the model's resilience, various operations were performed on the training images, including rotation, scaling, and flipping.

3.2.3 MobileNet:

For effective model performance in embedded and mobile vision applications, MobileNet was created. The Fruit-360 dataset's 36 classes were used to train the MobileNetV2 model for this study, which placed an emphasis on both accuracy and computational efficiency.

Architecture Details:

Pre-trained Model: The MobileNetV2 model, which is akin to Inception V3, was obtained from the ImageNet dataset and came with pre-trained weights.

Layer Configuration: After removing the top classification layers, two dense layers with ReLU activation (128 units each) were added. A softmax layer with 36 units for classification was then added.

Input Size: The Fruit-360 dataset was deemed appropriate for the model's input size, which was set to accommodate 224x224x3 images.

Training details:

Optimizer: The loss function utilized in the training process was categorical cross-entropy, which was trained using the Adam optimizer.

Fine-tuning: To ensure high accuracy at low computational costs, the pre-trained model was adjusted to fit the particular fruit recognition task.

3.2.4 YoloV5:

The You Only Look Once (YOLOv5) models are well-known for their ability to detect objects in real-time. Yolov5, in particular, strikes a balance between speed and accuracy, which makes it appropriate for applications that need instantaneous results in recognition. **Architecture Details:**

Detection Capabilities: YOLOv5 is able to identify various objects in an image and provides class labels and bounding boxes for each one that is found. This skill is essential for concurrently recognizing various fruits on a plate.

Network Design: The model comprises a head for detection, a neck for feature pyramid networks, and a backbone for feature extraction.

Training details:

Dataset: Using a customized dataset of pictures of different fruits marked with bounding boxes and class labels, the model was trained.

Augmentation and Regularization: To improve the model's resilience and capacity for generalization, strategies like mixup, label smoothing, and mosaic augmentation were applied.

3.2.5 YoloV8:

The most recent version of the YOLO series, YOLOv8, incorporates enhanced model architecture and training methods to further improve detection performance. **Architecture Details:**

Advanced Features: To improve feature representation and aggregation, YOLOv8 includes enhancements like CSPNet (Cross Stage Partial Networks) and PANet (Path Aggregation Network). **Scalability:** The model can be effectively applied to a wide range of hardware platforms, including mobile devices and high-performance servers. **Training details:**

Parameter Optimization: To optimize performance, a number of training parameters were carefully adjusted, including batch size, image size, number of epochs, and optimizer settings. **Automatic Mixed Precision (AMP):** AMP was applied to optimize memory usage and hasten training, resulting in quicker convergence and lower resource consumption.

The image recognition module achieves precise and effective fruit recognition by utilizing a blend of conventional and cutting-edge deep learning models. The distinct architecture and training methodology of each model enhance the overall resilience of the meal recommender system, guaranteeing accurate identification of fruits and vegetables in childcare environments. The combination of CNN, Inception V3, MobileNet, YOLOv5, and YOLOv8 models offers a complete solution that can handle different aspects of the fruit recognition task, such as real-time performance and high accuracy.

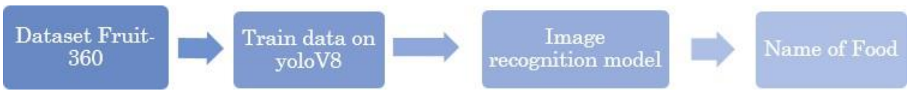

Figure 3.1: Flow diagram of image Recognition

3.3 Image segmentation module

The objective of this project's image segmentation procedure is to precisely locate and quantify the area occupied by food items in an image. This is a multi-step process that includes area calculation, thresholding, contour detection, and preprocessing. A thorough description of each step and the matching code implementation can be found below.

3.3.1 Image Preprocessing:

To improve the features needed for segmentation, the input image must first be preprocessed.

Convert to Grayscale: By eliminating color information, the image is transformed to grayscale in order to streamline the processing.

Median Blur: Applying a median blur filter can help to smoothen the image and cut down on noise.

3.3.2 Thresholding and Contour Detection:

Adaptive Thresholding: Gaussian thresholding that adapts to changing lighting conditions is known as adaptive thresholding.

Find Contours: The binary image’s contours are identified. The boundaries of the objects in the picture are represented by these contours.

3.3.3 Identifying the Largest Contour

A mask is made by identifying the largest contour, which is the combined area of the food and the plate.

Sort Contours: The largest contour is chosen after the contours are sorted according to area.

Create Mask: To separate the food and plate from the background, a mask is made using the largest contour.

3.3.4 Removing the Plate

By converting to the HSV color space and using thresholding on the S channel, the plate is eliminated from the picture.

Convert to HSV: To distinguish the plate from the food based on color information, the image is converted to an HSV color space.

Thresholding in S Channel: To remove the plate, Otsu thresholding is applied to the S channel.

3.3.5 Removing Skin Pixels

HSV color space thresholding is used to identify and eliminate skin pixels.

Convert to HSV: In order to identify skin pixels, the image is converted to an HSV color space.

Thresholding for Skin: Based on HSV values, a mask is made to identify skin pixels, which are subsequently eliminated.

We know the size of the thumb is approximately 5*3cm, so by keeping it as a reference we can calculate the actual area of fruit as follows.

$$\text{Actual food Area} = \frac{\text{pixel area of fruit} \times \text{size of thumb}}{\text{pixel area of thumb}} \tag{3.3.1}$$

From the actual food area, we can calculate the volume of food according to the shape of fruit. From the volume of food, we can calculate weight by multiplying volume with density.

Figure 3.2: Flow diagram of image Segmentation

3.4 Database module

3.4.1 Open Food Facts

A vast, user-generated database called OpenFoodFacts is devoted to listing food items from all over the world. Through the provision of comprehensive information about the nutritional value, ingredients, and sustainability of various food items, the platform seeks to empower consumers. By scanning barcodes, taking pictures of products, and entering data, users can help build a comprehensive and collaborative database of food-related knowledge. By enabling consumers to base their dietary decisions on accurate and current information, OpenFoodFacts promotes transparency in the food industry.

A multitude of details about each product, including nutritional values for calories, fats, carbs, proteins, vitamins, and minerals, are available on the website. It also provides information on ingredient lists, possible allergies, and additives, which makes it an invaluable tool for people who follow particular dietary regimens. OpenFoodFacts is noteworthy for its focus on environmental impact and sustainability. Among other things, it offers information on packaging, carbon footprint, and the use of palm oil. This emphasis assists users in managing their health as well as the environmental effects of the food choices they make.

Additionally, OpenFoodFacts has a number of features and tools to improve user interaction and experience. During shopping, consumers can quickly access product information by scanning product barcodes with ease using the platform's mobile app. The website is available to a worldwide audience because it supports several languages. Furthermore, through its open API, OpenFoodFacts uses its data to power other apps and services, such as food scoring systems and diet trackers. This transparency and dedication to data sharing support the development of an expanding ecosystem of applications designed to raise food literacy and encourage more sustainable, healthful eating practices.

3.4.2 Data Scrapping:

The OpenFoodFacts website has a large database of food products, and the purpose of the web scraping is to extract nutritional information from it. The bs4 module's BeautifulSoup for HTML content parsing, pandas for data manipulation and storage, and requests for sending HTTP requests are just a few of the Python libraries that are used. Furthermore, it makes use of concurrent. futures for parallel processing, greatly raising the process's effectiveness in data scraping.

To create complete URLs for each product page, it starts by defining the OpenFoodFacts website's primary URL and a base URL. The function scrape page is one of its features; it accepts a page number as an input and retrieves nutritional information from that particular page. Using BeautifulSoup, the HTML content of the page is parsed after an HTTP GET request is made to the page URL and the response is successful (status code 200). It looks through all anchor (. <a>) tags to denote links to specific product pages, namely those that begin with /product/. After extracting the product URLs, it goes through each URL and makes a new HTTP GET request to get the content of the product page.

In the event that it finds a table with the nutritional information, it parses the product page. Next, the product name is presumed to be within an extraction of the nutritional data that is then saved in a dictionary. <h1> attach tag. The data for all products is compiled into a list called nutrition data, to which this dictionary is appended.

To summarize, this web scraping script navigates through various pages and product links to methodically extract nutritional information from the OpenFoodFacts website. It then parses the relevant HTML content and stores the extracted data in a structured format. The script can handle large-scale data extraction tasks because of its ability to handle large volumes of data efficiently through the use of parallel processing.

3.4.3 Preprocessing of Data

In order to prepare the nutritional data that was scraped for additional analysis, it is intended to be cleaned and filtered. Filtering rows according to the existence of reliable nutrition data and eliminating units from numerical values are the preprocessing procedures. First, it defines a function called remove units, which matches numerical values—which may or may not include commas and decimal points—using a regular expression. Only the numerical portion of the values remains after this function removes the units.

The function gives the numerical value back if a match is found; if not, it gives None. To decide whether a row should be retained in the final dataset, another function called should keeprow assesses every row. Only rows with adequate information are kept by calculating the percentage of non-empty nutrient values (apart from the first column, which is presumed to be empty). This ensures that at least 70% of the nutrient columns have data. The CSV file nutrition data is read as input. the data is stored in a list in csv using the csv module. Afterwards, the row is filtered. It opens nutrition data, the input **CSV!** (CSV!) file. csv, which stores the data in a list using the csv module. After that, it applies the should keep row function to filter the rows, keeping only those that satisfy the requirement for having sufficient nutrient data. The script iterates through the columns (apart from the first one) for each row in the filtered data, using the remove units function to eliminate any units from the numerical values. The nutrient values are standardized in this step, which makes them more consistent and manageable for use in later analyses. Ultimately, nutrition data processed final, a new CSV file, contains the data that has been cleaned and filtered.

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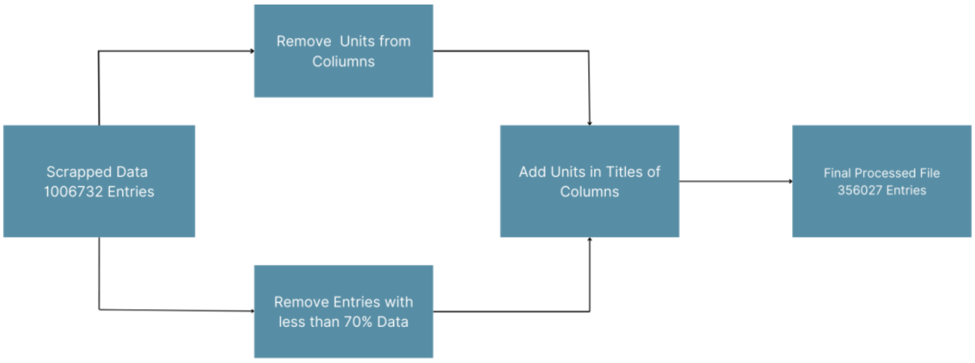

Figure 3.3: Preprocessing steps of scrapped data

3.4.4 Collected Database

I have collected the database of micronutrients value from the dietician. The provided dataset includes detailed dietary requirements broken down by age groups, encompassing a wide range of nutrients necessary at different phases of life. It highlights the various nutritional needs based on age and gender and includes data for males, females, infants, and children. These reflect the dietary guidelines for the best possible health and development and include essential nutrients like water, calories, protein, carbs, fiber, fats, vitamins A, B3, B6, B9, C, and E, and minerals calcium, iron, magnesium, potassium, sodium, zinc, choline, and selenium. The dataset for infants differentiates between 0-0.5 years and 0.5-1 year, outlining requirements for the first year of life. The data for the age groups 1-3 and 4-8 years shows how children's nutritional needs change as they get older.

The dataset, which takes into account the variations in nutritional needs throughout adolescence, adulthood, and senior years, offers comprehensive requirements for both males and females from ages 9 through over 70. With each nutrient's exact value provided, it is ensured that following the dietary recommendations will support growth, development, and general health throughout the life cycle. This dataset, which was gathered from a dietitian, is a useful tool for comprehending and creating balanced diet plans that are catered to particular age and gender groups and support long-term health and wellbeing.

3.4.5 Image Processing and Nutrient Calculation

Our system analyzes user-submitted photos of their meals to extract pertinent nutritional data. The two primary modules involved in this are image segmentation and image recognition.

Image Segmentation:

The mass of the food items is first ascertained by analyzing the uploaded image. Different meal components are identified and isolated using image segmentation techniques. This lets us calculate the approximate weight (in grams) of every food item in the picture.

Image Recognition:

The food items in the divided sections are identified by the image recognition module following segmentation. In this step, machine learning models trained on labeled food images are used to compare the visual properties of the food in the image with a database of known food items.

The meal's nutritional values can now be determined using the identified food items and their estimated masses. The processed dataset from Open Food Facts is used to match the identified food items to the relevant entries in our dataset. The dataset offers nutrient values per 100 grams; therefore, we scale these values based on the actual mass of the food items in the uploaded picture. The accurate nutrient content for a given quantity, such as 150 grams of food, is obtained by multiplying the nutrient values by 1.5.

3.4.6 Nutrient Log:

The time of consumption and the computed nutritional data are recorded for every meal. By keeping track of the user's food consumption, this nutrient log makes it possible to monitor their dietary practices in great detail over time. Our system has the ability to offer customized meal recommendations based on the total nutrient log. We are able to determine dietary excesses or deficiencies by examining the logged data and making recommendations for foods that might help the user maintain a balanced diet. The system will suggest foods high in iron to fill the gap, for instance, if the log shows a deficiency in this mineral.

By following this rigorous process, we make sure that our meal recommendation system is reliable, accurate, and able to offer insightful nutritional data. A comprehensive pipeline that provides users with precise and customized dietary recommendations is formed by the integration of web scraping, data preprocessing, image processing, and nutrient calculation. In order to produce a user-friendly and efficient nutritional guidance tool, this method not only makes use of the extensive nutrient data from Open Food Facts but also incorporates sophisticated image analysis techniques.

Figure 3.4: Flow diagram of DataBase Module

3.5 Recommendation module

Our meal recommender system's recommendation module is a vital part that gives users individualized dietary advice based on their nutritional needs and deficiencies. This module combines the user's dietary intake information, assesses their demographics, and recommends foods to help fill in any nutrient deficiencies. The procedure is segmented into multiple distinct phases:

3.5.1 User Demographic Data Collection

Age and Weight Input: The initial stage of the recommendation module entails gathering crucial demographic data from the user, particularly their age and weight. These are important inputs because they determine how different the requirements are for nutrients. Weight affects the recommended daily intake of different nutrients, whereas age determines the user's life stage (infant, child, adolescent, adult, or senior).

3.5.2 Nutrient Requirement Analysis

Determining Nutrient Requirements: We consult established nutritional standards and dietary guidelines, such as those issued by national dietary guidelines or health organizations like the World Health Organization (WHO), using the age and weight data. These recommendations provide adequate intakes (AIs) or recommended daily allowances (RDAs) for a range of nutrients, based on body weight and age groups. To enable fast lookups, we store these requirements in an organized format, usually a CSV file or database table.

3.5.3 Dietary Intake Calculation

Nutrient Value Log Analysis: The nutrient value log, which documents the nutrient composition of each meal the user consumes, is used to track the user's dietary intake. Every time a user uploads a picture of their meal, the image processing module determines the nutritional values and updates this log. Because the log entries have timestamps, we can examine intake patterns over particular time periods (e.g. g. weekly, daily).

Total Nutrient Intake Calculation: We total the nutrient values noted in the log over a predetermined time period to determine the user's overall nutrient intake. To do this, the quantities of every nutrient (e.g. g. , grams of calcium, milligrams of protein) from each meal that was recorded. The end product is a detailed breakdown of the user's nutrient consumption by nutrient.

3.5.4 Deficiency Detection

Calculating Deficiencies: After determining the overall intake, the following stage is to pinpoint any deficiencies. To do this, deduct each nutrient's total intake from the corresponding nutrient requirement. The difference indicates whether the user is getting the recommended amount of each nutrient, meeting it, or falling short of it. Negative values denote deficiencies, zero indicates sufficient intake, and positive values indicate excess intake.

Identifying Key Deficiencies: We give critical deficiency of certain nutrients priority over others because their effects on health are not all the same. The degree of the deficiency and the nutrient's significance for the user's health may be taken into consideration when determining this prioritization. For example, a severe iron or calcium deficiency might be more serious than a small vitamin C deficiency. To determine which nutrients are most deficient and require attention, we rank the deficiencies.

3.5.5 Food Recommendation

Matching Foods to Nutrient Needs: Matching Foods to Nutrient Needs: The next step is to find foods that are rich in the deficient nutrients on our prioritized list. We make use of our processed Open Food Facts dataset, which includes thorough nutrient profiles for a range of foods. We can identify foods with high concentrations of the deficient nutrients by running queries against this dataset. For instance, we look for foods with a high iron content if the user is iron deficient.

Generating Personalized Recommendations: We provide the user with customized food suggestions based on the found nutrient-rich foods. These suggestions are customized based on the individual needs and preferences of the user. By using the system to rank the foods based on their nutrient density, the most nutrient-dense options will always be shown first. Furthermore, in order to make the recommendations more applicable and useful, we take into account variables like dietary restrictions, allergies, and cultural preferences.

Recommendation Presentation: The user is provided with the final recommendations in an approachable manner, typically through a mobile application or online interface. Details like the food's name, nutritional value, serving size, and suggested preparation methods might all be included in the recommendations. We might also include more details about how these foods help the user achieve their nutritional goals and provide advice on how to include them in regular meals.

3.5.6 Continuous Improvement

Feedback Loop: We include a feedback loop in order to continuously improve the recommendation module. Users are able to comment on the suggestions they receive, including whether they are happy with the foods that are recommended and whether their nutritional status has changed. The recommendation algorithms are improved by this feedback, which also makes future suggestions more accurate and pertinent.

Data Update and Maintenance: To keep recommendations current and accurate, it's critical to regularly update the nutrient dataset and dietary guidelines. Based on the most recent dietary guidelines and scientific research, we regularly update our nutrient requirement references and refresh the data from Open Food Facts.

Our meal recommender system's recommendation module uses a thorough and data-driven methodology to offer tailored dietary recommendations. We assist users in achieving balanced nutrition and addressing particular deficiencies by combining user demographics, a thorough nutrient intake analysis, and targeted food recommendations. By ensuring that users receive practical and actionable dietary guidance, this holistic methodology promotes their overall health and well-being. We work hard to improve the efficacy and precision of our recommendations via user feedback and ongoing development, which makes the system a useful tool for individualized nutrition management.

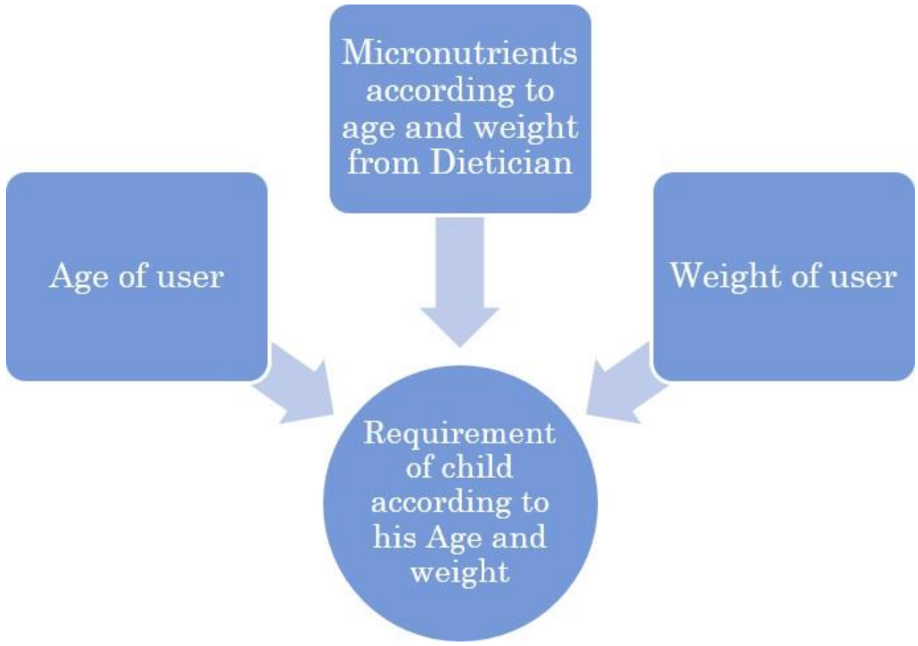

Figure 3.5: Inputs flow diagram

Figure 3.6: Flow diagram of Recommendation module

3.5.7 Flow Diagram

The work flow diagram for complete system is shown in figure.

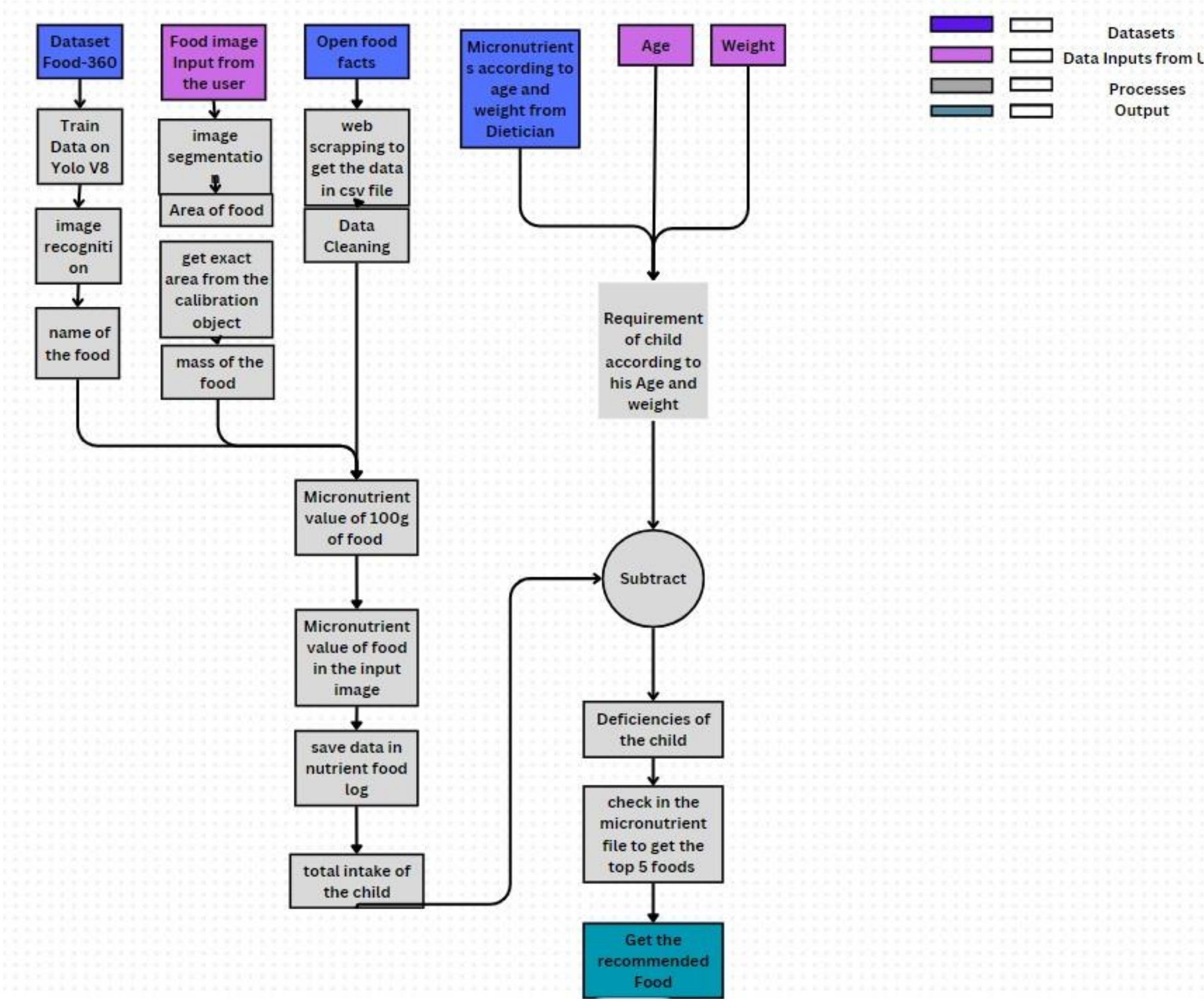

Figure 3.7: Work flow diagram of whole process

CHAPTER 4

Chapter 4: Results

4.1 Image recognition

The meal recommender system's image recognition module is a vital part since it accurately recognizes food items from photos, which is necessary for calculating their nutritional value and generating individualized dietary recommendations. To achieve the highest level of accuracy, a variety of machine learning models and datasets were tested during the development and testing of this module. Below are the findings from these experiments.

4.1.1 Initial Experiments with CNN

Testing with 7 Classes from the FOODD Dataset In the first stage of the experiment, a CNN model was created and tested using 7 classes from the FOODD dataset. Models for food recognition training and evaluation are frequently conducted using the FOODD dataset, which is an extensive collection of food photos. This dataset showed an accuracy of 86% for the CNN model, suggesting that it has the potential to recognize food effectively.

Testing with 15 Classes from the FOODD Dataset The CNN model was further trained with 15 classes from the FOODD dataset after the preliminary results were encouraging. But this resulted in overfitting, a prevalent issue in machine learning where the model works well on training data but badly on fresh, untested data. Early stopping, Dropout, and L2 Regularization were some of the techniques used to reduce overfitting. These techniques keep the model from picking up noise from the training set, which aids in the model's generalization. Even with these efforts, only 70 percent accuracy was reached, indicating the need for stronger models or more thorough data preprocessing.

```
Epoch 1/15
108/108 [==============================] - 1176s 11s/step - loss: 4.8774 - accuracy: 0.0961 - val_loss: 2.5452 - val_accuracy:
0.1511
Epoch 2/15
108/108 [==============================] - 1258s 12s/step - loss: 2.4253 - accuracy: 0.2102 - val_loss: 2.1053 - val_accuracy:
0.3630
Epoch 3/15
108/108 [==============================] - 1166s 11s/step - loss: 1.7605 - accuracy: 0.4256 - val_loss: 1.5741 - val_accuracy:
0.4953
Epoch 4/15
108/108 [==============================] - 1013s 9s/step - loss: 1.1828 - accuracy: 0.6097 - val_loss: 1.3282 - val_accuracy:
0.6046
Epoch 5/15
108/108 [==============================] - 1001s 9s/step - loss: 0.7861 - accuracy: 0.7342 - val_loss: 1.2789 - val_accuracy:
0.6073
Epoch 6/15
108/108 [==============================] - 951s 9s/step - loss: 0.5963 - accuracy: 0.8014 - val_loss: 1.4385 - val_accuracy: 0.
6140
Epoch 7/15
108/108 [==============================] - 919s 9s/step - loss: 0.5399 - accuracy: 0.8257 - val_loss: 1.3116 - val_accuracy: 0.
6478
Epoch 8/15
108/108 [==============================] - 918s 9s/step - loss: 0.4486 - accuracy: 0.8518 - val_loss: 1.4777 - val_accuracy: 0.
6262
Epoch 9/15
108/108 [==============================] - 920s 9s/step - loss: 0.4016 - accuracy: 0.8616 - val_loss: 1.3975 - val_accuracy: 0.
6086
Epoch 10/15
108/108 [==============================] - 914s 8s/step - loss: 0.3650 - accuracy: 0.8726 - val_loss: 1.4544 - val_accuracy: 0.
6437
Epoch 11/15
108/108 [==============================] - 915s 8s/step - loss: 0.2914 - accuracy: 0.8998 - val_loss: 1.3726 - val_accuracy: 0.
6356
Epoch 12/15
108/108 [==============================] - 921s 9s/step - loss: 0.3183 - accuracy: 0.8917 - val_loss: 1.5410 - val_accuracy: 0.
5897
Epoch 13/15
108/108 [==============================] - 909s 8s/step - loss: 0.2580 - accuracy: 0.9097 - val_loss: 1.6717 - val_accuracy: 0.
6167
Epoch 14/15
108/108 [==============================] - 899s 8s/step - loss: 0.2846 - accuracy: 0.8964 - val_loss: 1.6374 - val_accuracy: 0.
6154
Epoch 15/15
108/108 [==============================] - 901s 8s/step - loss: 0.2214 - accuracy: 0.9201 - val_loss: 1.6168 - val_accuracy: 0.
6491
```

Figure 4.1: CNN with 15 classes training

4.1.2 Experiments with InceptionV3

Training on 36 Classes from the Fruit-360 Dataset The InceptionV3 model, which is renowned for its effectiveness in image classification tasks, was used in the following stage. Another popular dataset for fruit image recognition, Fruit-360, provided 36 classes for this model to be trained on. Although an improvement, the InceptionV3 model's accuracy of 71% was still insufficient for our requirements. The outcomes made clear how difficult it is to scale food recognition models so they can efficiently manage more classes.Here is the result of training Accuracy of Inception-V3

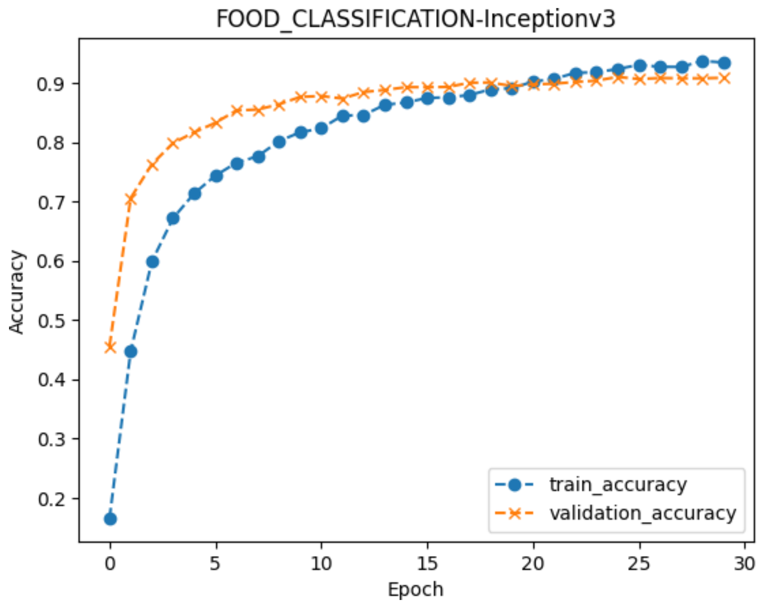

Figure 4.2: Inception V3 Training Accuracy

Here is the result of training Loss of Inception-V3

Here are two examples showing the results of Inception V3 model.

4.1.3 Experiments with MobileNet

Training on 36 Classes from the Fruit-360 Dataset MobileNet training experiments on 36 classes from the Fruit-360 dataset The MobileNet model was trained on the same 36 classes from the Fruit-360 dataset as the InceptionV3 experiments. Because of its efficient and lightweight design, MobileNet can be deployed on devices with constrained computational power. With an accuracy of 87%, the model produced results that were much better than those of earlier

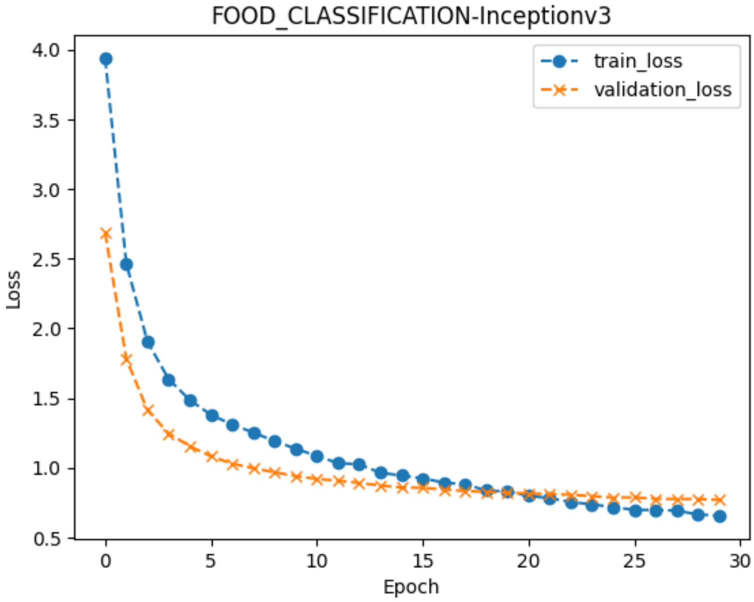

Figure 4.3: Inception V3 training loss

Figure 4.4: Example 1 of Inception V3 results

Figure 4.5: Example 2 of Inception V3 results

attempts. It was observed, nevertheless, that MobileNet had trouble identifying several fruits in a single image—a situation that frequently occurs in practical applications.

4.1.4 Experiments with YOLO Models

YOLOv5 Training on 17 Classes from the Fruit-360 Dataset: The YOLO (You Only Look Once) model was created in order to overcome MobileNet's shortcomings in multi-object detection. Yolo is renowned for its ability to simultaneously detect multiple objects. YOLOv5 was initially trained using 17 classes from the Fruit-360 dataset. With an accuracy of 85%, the model demonstrated excellent performance. The results of this performance suggested that YOLO models could manage the intricacy of multiple-item food recognition tasks.

YOLOv8 Training on 21 Classes from the Fruit-360 Dataset: Training of the Newest Yolo model, YOLOv8, on 21 Classes from the Fruit-360 Dataset: In order to improve accuracy even more, the newest Yolo model, YOLOv8, was trained and evaluated on 21 classes from the Fruit-360 dataset. Better architecture and optimization methods are just two of the improvements that YOLOv8 brings over from its predecessors. It became the most accurate model tested to date, achieving an astounding 92 percent accuracy. For the image recognition module of the meal recommender system, YOLOv8 is the best option due to its excellent accuracy and resilience in identifying various food items in images.

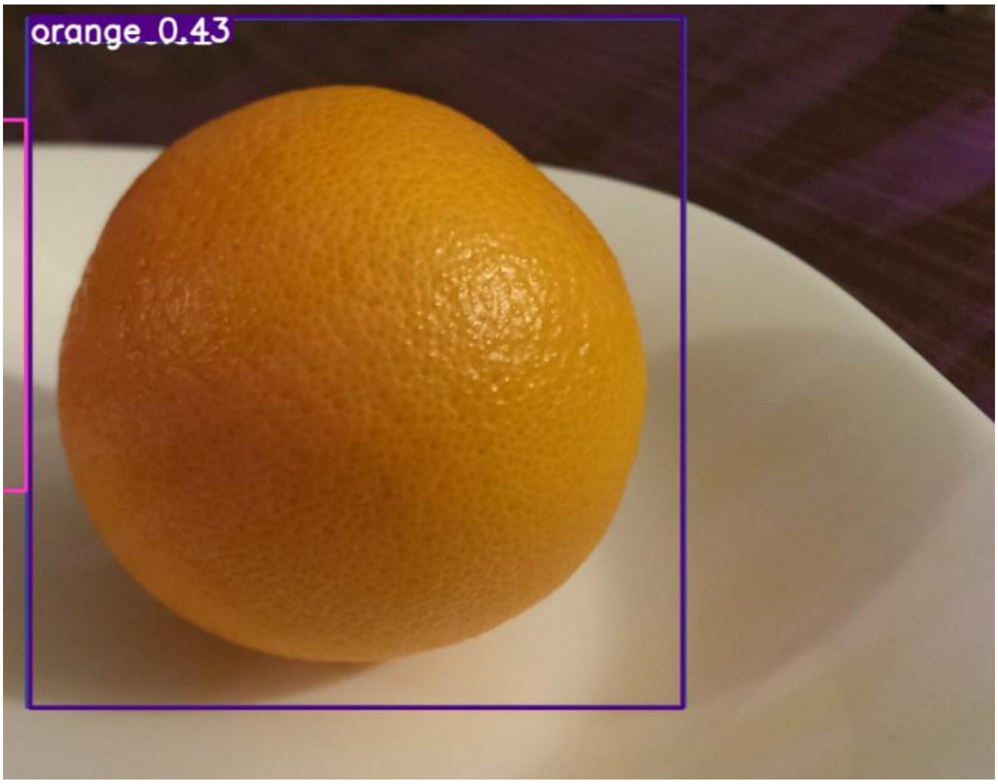

Figure 4.6: Detected from yoloV8

```
Detected: orange, Confidence: 0.43186184763908386
Detected: lemon, Confidence: 0.316614031791687
```

Figure 4.7: Output from yoloV8

4.1.5 Final Model Selection

The YOLOv8 model was chosen as the meal recommender system's final image recognition model because of its better accuracy and capacity for multi-object detection. The ability of this model to precisely identify different food items in an image is essential for figuring out their nutritional value and making appropriate dietary recommendations.

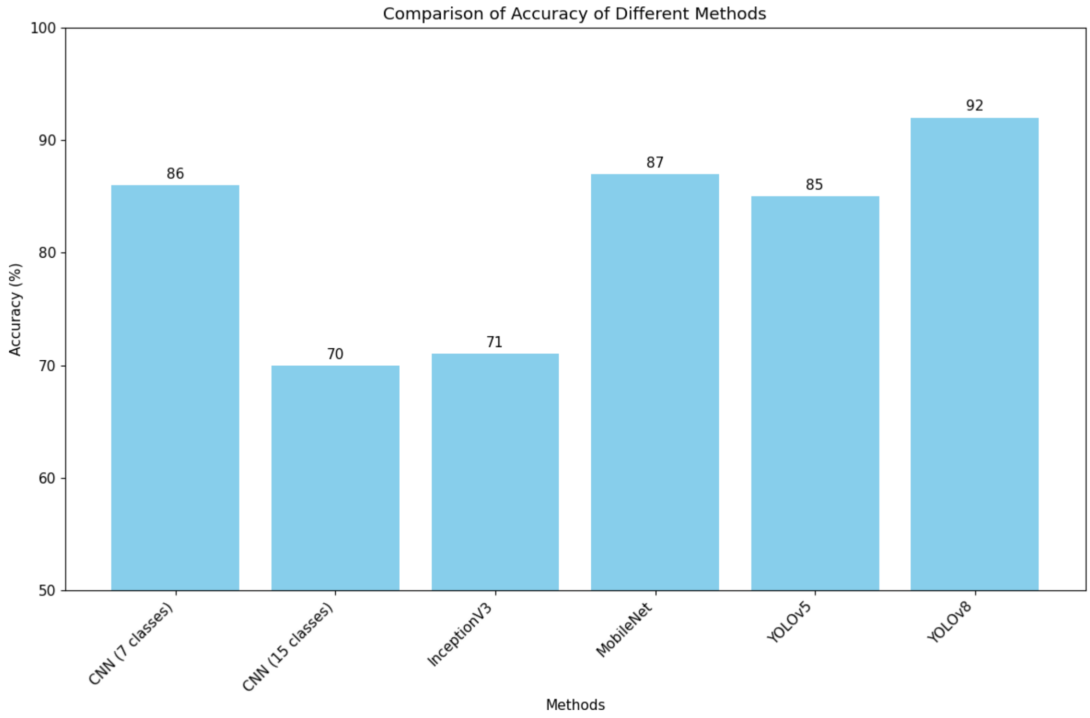

Figure 4.8: Accuracy Comparison for methods for image Recognition

Extensive testing and analysis of multiple models and datasets were conducted during the development of the image recognition tool. A strong basis for precise nutrient analysis and individualized dietary recommendations is provided by the meal recommender system's ability to accurately recognize a broad variety of food items, which is ensured by the final model chosen, YOLOv8.

4.2 Image segmentation

Another essential part of the meal recommender system is the image segmentation module, which is meant to precisely ascertain the food item's mass once the image recognition module has identified it. There are multiple steps in the process, which include calculating the food's area and volume, applying filters and thresholding techniques, and using calibration objects. The comprehensive outcomes of these tests are displayed beneath.

4.2.1 Calibration and Segmentation

Using the Thumb as a Calibration Object: Accurately segmenting food items from images requires the use of a dependable calibration object. Here, the user's thumb serves as the calibration object. The other objects in the picture can be scaled using the thumb, which offers a known reference size. This novel method enables precise measurement of the food item's mass and size regardless of changes in camera angle or distance.

4.2.2 Applying Filters and Thresholding Methods

Initial Image Processing: Applying different filters to the image to improve the contrast and edges between the food item and the background is the first step in the segmentation process. The image is preprocessed using filters like edge detection, median blur, and Gaussian blur. This preprocessing stage is essential to raising the accuracy of the segmentation methods that follow.

Thresholding Techniques: Following the filtering process, the food item is separated from the background using thresholding techniques. Through thresholding, the grayscale image is transformed into a binary image in which the intensity values of the pixels determine whether they are in the foreground (food item) or background. To dynamically find the ideal threshold values, methods like Otsu's thresholding and adaptive thresholding are used. These techniques aid in precisely identifying the food item, even in pictures with complicated backgrounds and uneven lighting.

4.2.3 Pixel Area Calculation

Segmentation Results: The pixel areas of the fruit and the skin are computed after the food item has been segmented. The precision of the pixel classification is the basis for evaluating the segmentation outcomes. After the image has been segmented, any noise or tiny artifacts that might have been mistakenly identified as a component of the food item are removed through processing.

Area Computation: The following step is to calculate the segmented food item's area in pixels. The area calculation is necessary to calculate the food item's volume and, in turn, its mass. Through manual measurements and comparison with established reference objects, the area computation's accuracy is confirmed.

4.2.4 Volume and Mass Calculation:

Volume Estimation Estimating the food item's volume involves using the pixel area that is obtained during the segmentation process. The assumption behind the volume calculation is that the food item has a consistent thickness or shape. For instance, it is common knowledge that fruits like oranges and apples have a roughly spherical shape, but items like fish fillets and bread slices may be more accurately estimated to have a more uniform thickness.

Spherical Items (e.g., Apples, Oranges): Sphere-shaped objects (e.g. g. , Apples, Oranges): The formula for a sphere's volume can be applied to fruits and vegetables that resemble spheres:

$$V = \frac{4}{3}\pi r^3$$

Here, r is the radius of the sphere, which can be calculated from the pixel area assuming the fruit is circular in the top-down view:

$$r = \sqrt{\frac{\text{pixel area}}{\pi}}$$

Substituting r into the volume formula, we get:

$$V = \frac{4}{3}\pi \left(\sqrt{\frac{\text{pixel area}}{\pi}}\right)^3$$

Cylindrical Items (Carrot, Cucumber

For items that are more uniform in thickness, a cylindrical approximation can be used. The volume of a cylinder is given by:

$$V = \pi r^2 h$$

Here, r is the radius calculated from the pixel area, and h is the assumed or measured thickness of the item.

Other Shapes

For irregularly shaped items, more complex volume estimation techniques might be needed. This can involve using multiple images from different angles or employing 3D scanning techniques.

Mass Calculation

Once the volume is estimated, the mass of the food item can be calculated using its density. The density (ρ) of various food items is well-documented in nutritional databases.

$$\text{Mass} = \text{Volume} \times \text{Density}$$

Example Calculation

Let's assume we are working with an orange, which is approximately spherical:

Step 1: Calculate the radius

Suppose the pixel area obtained from the segmentation process is 5000 pixels. Convert pixel area to actual area using the pixel-to-cm conversion factor (cm^2/pixel):

$$\text{actual area} = 5000 \times (\text{pixel-to-cm multiplier})^2$$

If the pixel-to-cm multiplier is 0.1 cm/pixel, then:

$$\text{actual area} = 5000 \times 0.1^2 = 5000 \times 0.01 = 50\,\text{cm}^2$$

Step 2: Calculate the radius

$$r = \sqrt{\frac{50}{\pi}} \approx 3.99\,\text{cm}$$

Step 3: Calculate the volume

$$V = \frac{4}{3}\pi(3.99)^3 \approx \frac{4}{3}\pi(63.51) \approx 267\,\text{cm}^3$$

Step 4: Calculate the mass

Assume the density of the orange is 0.96 g/cm^3:

$$\text{Mass} = 267 \times 0.96 \approx 256.32 \text{ grams}$$

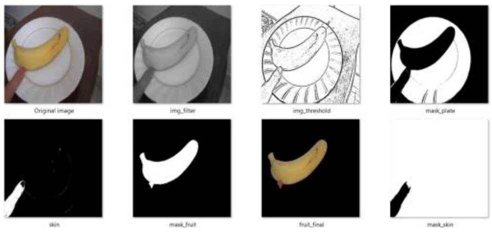

Figure 4.9: Image segmentation method

```
Fruit_name:  orange fruit_calories:  2.516889896035589 kcal fruit_mass:  5.355084885182105 g
```

Figure 4.10: Quantitative output of image segmentation

4.3 Database module

The next step is to ascertain the fruit's nutritional value after utilizing the image segmentation and image recognition modules to identify the fruit's name and mass, respectively. Utilizing the Open Food Facts database to obtain comprehensive micronutrient data is accomplished through the Database Module. The dietary intake of the user is comprehensively recorded in the system by entering the retrieved data, along with the time of consumption.

4.3.1 Approach

To guarantee precise nutritional data retrieval and logging, the Database Module goes through a number of important phases. Here is a thorough explanation of each step:

Step 1 - Query Construction: The Database Module creates a query to search the Open Food Facts database after receiving the fruit's name and mass. To eliminate doubt and guarantee that the right nutritional profile is obtained, the query is made to be specifically tailored to the fruit that has been identified. The name of the fruit must be included as a parameter in a URL or API call to accomplish this.

Step 2- API Call and Data Retrieval: An API call is made with the created query to the Open Food Facts database. In response, the database returns a JSON object with comprehensive details about the fruit, including its micronutrient values. In order to extract pertinent data fields like vitamins, minerals, and other nutritional content, this step entails parsing the JSON response.

Step 3 - Nutrient Calculation Based on Mass: Given that the image segmentation module has established the fruit's actual mass, the database module computes the nutrient content in a proportionate manner. In the event that the database provides values per 100 grams and the orange weighs 150 grams, the nutrient values are scaled appropriately. If 150 grams have 50 mg of vitamin C, then the amount would be as follows.

Step 4- Logging the Data: The name of the fruit and the time it was consumed are noted in the food log along with the estimated nutrient values. A database is used to efficiently store and retrieve this log, which is kept in an organized manner. Some of the fields that are included in the food log entry are:

- **Timestamp:** The date and time when the fruit was consumed.
- **Fruit Name:** The name of the identified fruit (e.g., Orange).
- **Mass:** The mass of the fruit as determined by the segmentation module (e.g., 150 grams).
- **Nutrient Values:** Calculated values for various nutrients (e.g., Vitamin C: 75 mg).

This structured logging guarantees that the user's dietary intake is tracked precisely over time, offering useful information for dietary recommendations and health monitoring.

timestamp	3/19/2024 13:23	3/19/2024 13:24	3/19/2024 13:25	3/19/2024 13:26	3/19/2024 13:27
fruit_name	apple	orange	banana	grape	watermelon
mass	79	97	101	88	96
energy(g)	115.34	186.24	1420.06	0	329.28
energy-from-fat(g)					
fat(g)	0	0.194	1.0807	0	0.384
saturated-fat(g)	0	0.097	0		0.288
fiber(g)	2.528	0	1.818		0
proteins(g)	0	0.679	0	0	0.096
casein(g)					
serum-proteins(g)					
nucleotides(g)					
salt(g)	0	0.00291	0.0179578	2.794	0
sodium(g)	0	0.001145669	0.00707	1.1	0
alcohol(g)	2.765				
vitamin-a(g)	1.54E-05		0		0.000202752
beta-carotene(g)					
vitamin-d(g)					
vitamin-e(g)					
vitamin-k(g)					
vitamin-c(g)	0.002449	0.0194	0.002121	0.88	0.010176
vitamin-b1(g)				1.1	
vitamin-b2(g)				2.49333304	
vitamin-pp(g)				0.14666696	
vitamin-b6(g)				0.01466696	
vitamin-b9(g)					
folates(g)					
vitamin-b12(g)				8.80E-05	
biotin(g)					
pantothenic-acid(g)				0.14666696	
silica(g)					
bicarbonate(g)					
potassium(g)	0.0869			1.46696	
chloride(g)					
calcium(g)	0		0	0.14696	0.01344
phosphorus(g)					
iron(g)	0.0001817		0.0019493		0.00024
magnesium(g)				0.11704	
zinc(g)				0.011	
copper(g)					
manganese(g)					
fruits-vegetables-nuts(g)		7.76			9.696
fruits-vegetables-nuts-estimate(g)		11.64			
collagen-meat-protein-ratio(g)					
cocoa(g)					
chlorophyl(g)					
carbon-footprint(g)					
nutrition-score-fr(g)	8.69	13.58	12.12		3.84
nutrition-score-uk(g)	0.79	1.94	12.12		3.84
glycemic-index(g)					

Figure 4.11: Food log

Step 5-Data Validation and Error Handling: The Database Module has data validation and error handling mechanisms as well. The method employs extra criteria, like brand or in-depth descriptions, to choose the best entry, for example, if the database query yields several results for a fruit name. The module also provides default nutrient values or asks the user for more information in situations where the database may not provide any results.

An essential part of the system that links nutritional analysis, segmentation, and image recognition is the database module. Through integration with the Open Food Facts database, users are guaranteed to obtain precise and comprehensive information regarding their food consumption. By going through this process, the user gains a better understanding of their eating habits and lays the groundwork for customized dietary advice and health interventions.

4.4 Recommendation module

Personalized dietary recommendations are given to users by the Final Recommendation Module. This module evaluates nutritional deficiencies and suggests foods that can help close these gaps by using the information gathered from earlier steps, such as the user's age, weight, and dietary intake. The module hopes to improve the user's overall nutritional status and encourage improved health outcomes by doing this.

4.4.1 Approach

The Final Recommendation Module employs a methodical and data-driven process to guarantee that the recommendations are customized to meet the individual needs of the user. Below is a thorough explanation of each step

Step 1- Obtaining User Information: The initial stage of the recommendation process involves obtaining the most important user data, such as weight and age. These factors determine how different the nutritional requirements are, so knowing this information is essential. For example, the requirements of vitamins, minerals, and other nutrients vary among children, adults, and the elderly.

```
Please Enter Age :3
Please Enter Weight in kgs :15
```

Figure 4.12: Obtaining User Input

Step 2- Calculating Nutritional Requirements: The module determines the user's daily micronutrient requirements based on the weight and age that were obtained. The World Health Organization (WHO) and the National Institutes of Health (NIH), among other health organizations, have established dietary guidelines and reference values that serve as the foundation for these calculations. The needs are established for numerous nutrients, such as vitamins (e.g. g. vitamins (A, C), minerals (e.g. g. , iron, calcium), as well as macronutrients (e.g. g. , fiber, and protein). For instance, the module will use the pertinent guidelines to calculate the user's daily requirements for nutrients like iron, calcium, and vitamin D.

```
print(requirements)

1-3
   Unnamed: 0 Age  Weight (kg)  Water(g)   energy(g)  Protein(g)  \
4           4  1-3           12       1.3  135.559508        1.05

   carbohydrates(g) Fiber(g) Fats (g)  choline mg  ...  vitamin-a(g)  \
4             130.0       19        -       200.0  ...        0.0006

   vitamin-b1(g)  vitamin-e(g)  vitamin-b2(g)  vitamin-pp(g)  vitamin-b6(g)  \
4         0.0005         0.006         0.0005          0.006         0.0005

   vitamin-b9(g)  vitamin-c(g)  vitamin-b12(g)  selenium(g)
4        0.00015         0.015          0.0009      0.00002

[1 rows x 26 columns]
   Unnamed: 0  Water(g)   energy(g)  Protein(g)  carbohydrates(g)  Fiber(g)  \
4           4       1.3  135.559508        1.05             130.0        19

   Fats (g)  choline mg  calcium(g)  iron(g)  ...  vitamin-a(g)  \
4       NaN       200.0         0.5    0.007  ...        0.0006

   vitamin-b1(g)  vitamin-e(g)  vitamin-b2(g)  vitamin-pp(g)  vitamin-b6(g)  \
4         0.0005         0.006         0.0005          0.006         0.0005

   vitamin-b9(g)  vitamin-c(g)  vitamin-b12(g)  selenium(g)
4        0.00015         0.015          0.0009      0.00002

[1 rows x 24 columns]
```

Figure 4.13: User's Dietiery Requirements

Step 3-Analyzing Dietary Intake: The module then uses the information from the food log to analyze the user's overall dietary intake. The user's complete food intake history, including food types and nutritional values, is kept in the food log. The module determines the total intake for each nutrient by adding up the nutritional values of all the foods that have been logged.

```
print(total_intake_cleaned)
```

```
mass                                   651.355085
energy(g)                             2061.201763
fat(g)                                   1.669410
saturated-fat(g)                         0.390355
fiber(g)                                 4.346000
proteins(g)                              0.812486
salt(g)                                  2.815028
sodium(g)                                1.108279
alcohol(g)                               2.765000
vitamin-a(g)                             0.000218
vitamin-c(g)                             0.915217
vitamin-b1(g)                            1.100000
vitamin-b2(g)                            2.493333
vitamin-pp(g)                            0.146667
vitamin-b6(g)                            0.014667
vitamin-b12(g)                           0.000088
pantothenic-acid(g)                      0.146667
potassium(g)                             1.553860
calcium(g)                               0.160400
iron(g)                                  0.002371
magnesium(g)                             0.117040
zinc(g)                                  0.011000
fruits-vegetables-nuts(g)               17.884407
fruits-vegetables-nuts-estimate(g)      12.282610
nutrition-score-fr(g)                   38.979712
nutrition-score-uk(g)                   18.797102
cholesterol(g)                           0.013376
carbohydrates(g)                       114.164433
sugars(g)                              100.305778
dtype: float64
```

Figure 4.14: User's Daily Intake

Step 4- Identifying Nutritional Deficiencies: The module then compares the user's total intake with their estimated requirements in order to identify any nutritional deficiencies. A deficiency is identified if the intake of a particular nutrient is less than what is necessary. For example, there is a 300 mg deficiency if the user requires 1000 mg of calcium per day but has only taken in 700 mg.

The following table shows a meal containing the elements covering the nutritional requirement.

```
You are deficient in these Nutrient values:
calcium(g) 0.31067551589839837
carbohydrates(g) 15.835566935999992
energy(g) 1925.6422549799997
fiber(g) 14.654
iron(g) 0.0046289999999999994
magnesium(g) 0.060075667530018015
potassium(g) 1.1574147597402995
sodium(g) 0.32477949913174897
vitamin-a(g) 0.00038184799999999995
vitamin-b1(g) 1.316000630131749
vitamin-b12(g) 0.00079467997478946
vitamin-b2(g) 2.9835677440985466
vitamin-b6(g) 0.0170536924018406
vitamin-c(g) 1.0734175211053991
vitamin-pp(g) 0.1695337682176505
zinc(g) 0.0101650061513174
```

Figure 4.15: Identifying Deficiencies

Step 5- Generating Food Recommendations: In order to compensate for these deficiencies, the module lists the top 10 foods that are high in the nutrients that are lacking. To do this, search for foods that have high concentrations of the necessary nutrients in a comprehensive food database, like the Open Food Facts database. Food accessibility and availability are taken into account during the selection process in addition to the nutrients they contain. Foods like dairy (milk, cheese, yogurt), leafy greens (kale, spinach), and fortified foods (cereals, orange juice) may be suggested by the module if the user is deficient in calcium.

```
The top 10 recommended foods for you are:
oat bran Khamiri roti (bagel) , 1item
chocolate snack cake cream filled w/frosting  , 1 slice
Potato Deep fries , 14 item
Apple juice , 0.5 cup
Apple steamed  , 1item
Human milk, Mature , 2 fluid oz
Doughnut,cake,chocolate glazed , 1item
corn bread 1 ,  مکئی ڈبل روٹی slice
beef ,vegetable  fajita  , 1item
Scone Biscuit  , 1item
```

Figure 4.16: Generating Recommendations

Step 6- Providing Recommendations to the User: At last, the module provides the user with these dietary suggestions in an understandable manner. One or more food lists, suggested serving sizes, and advice on how to incorporate these items into the user's diet could be included in the recommendations. Offering the user practical guidance to enhance their dietary intake is the aim. The recommendation could be something like this, for instance:

- **Calcium:** Increase intake by eating more dairy products, cheese, and yogurt. 2–3 servings should be your daily goal.
- **Iron:** Make sure your meals include more foods high in iron, such as red meat, lentils, and spinach.
- **Vitamin C:** Fruits like bell peppers, oranges, and strawberries will help you up your vitamin C intake.

One of the most important parts of the entire system is the Final Recommendation Module, which provides customized dietary recommendations by combining information from various sources. The tool aids users in achieving a balanced and healthful diet by precisely estimating nutritional deficiencies and making appropriate food suggestions. Through this process, long-term health and wellness are encouraged in addition to meeting immediate nutritional needs. To sum up, the Final Recommendation Module guarantees that specific dietary recommendations are given to users according to their individual profiles. Through the use of thorough data analysis and guidelines supported by evidence, the module offers users actionable and efficient dietary recommendations that they can readily incorporate into their daily routines.

CHAPTER 5

Chapter 5: Discussion and Analysis

5.1 Introduction

Addressing the nutritional needs of children in daycare centers is made possible in large part by the meal recommender system created for this project. With the system, working women will be able to keep an eye on and guarantee the right nutrition for their kids. The system enables the identification and nutritional analysis of meals automatically by integrating cutting-edge technologies like image recognition and segmentation. This complete dietary monitoring solution meets all requirements.

First, user input is collected by the system, in the form of pictures of the food items that the kids eat. While the image segmentation module determines the mass of the fruit, the image recognition module identifies it. Accurate identification and precise measurement of the amount of food consumed are guaranteed by this dual approach. The coherence and practicability of applying computer vision techniques to practical applications pertaining to nutrition and health are demonstrated by the integration of these modules into a unified system.

The system queries the Open Food Facts database to obtain comprehensive micronutrient information after obtaining the fruit's name and mass. This is an important step because it converts raw data into useful nutritional information that is logged for tracking purposes along with a timestamp. The food log acts as a historical record, making it possible to analyze trends and monitor development over time. This feature is especially helpful for parents and other caregivers who want to keep a close eye on their child's nutrition. The system's next crucial element is figuring out the right amount of nutrients for each age group. The system determines the daily requirements for micronutrients based on the age and weight of the child and standard nutritional guidelines.

5.2 Interpretation of results

This customized method guarantees that each child's nutritional analysis is pertinent and unique, improving the precision of identifying deficiencies. One of the main advantages of the system is its capacity to detect nutritional deficits. The technology is able to identify particular nutrients that the child's diet is deficient in by comparing the food log's recorded intake with the estimated requirements. This automated deficiency detection is an effective way to avoid long-term health problems linked to undernourishment.

Using the identified deficiencies as a starting point, the final recommendation module suggests foods high in the missing nutrients. The system creates a list of suggested foods by comparing the deficiencies with the nutritional values of different foods in the Open Food Facts database. In addition to addressing the deficiencies, this targeted recommendation approach encourages a diet that is balanced. Additionally, the system may become more efficient and user-friendly in the future if user preferences are added to the recommendation process.

5.3 Validation of results:

The following table shows validation of results by looking at the micro nutrients value of recommended food :

Nutrient	Total Intake	Requirement	Deficiency	oat bran Khamiri	chocolate snack cake	Potato Deep fries	Apple juice	Apple steamed	Human milk, Mature	Doughnut,	corn bread	beef, vegetable	Scone Biscuit
energy(g)	267.1276261	135.559508	131.56812	16.1116462	17.0188322	17.2780282	-0.088104	0.6894842	-1.7728778	15.33406	10.92773	44.1048142	11.96451
carbohydrates(g)	0.114164433	130	15.835567	18.38355669	10.38355669	4.383556694	-5.616443	-13.61644331	-15.61644331	4.383557	-1.616443	15.38355669	-0.61644
fiber(g)	4.346	19	14.654	3.2654	0.2654	2.2654	0.2654	0.2654	1.2654	1.2654	1.2654	3.2654	1.2654
iron(g)	2.37E-06	0.007	0.004629	-0.0006081	-0.0011181	-0.0017781	-0.002338	-0.0025481	0.0172019	-0.00185	-0.001788	0.0009419	-0.00149
vitamin-b2(g)	0.002984068	0.0005	0.0029836	0.000418357	0.000328357	0.000228357	0.0001984	0.000218357	0.000228357	0.000208	0.000338	0.000478357	0.000338
vitamin-b1(g)	0.001316501	0.0005	0.001316	4.66E-05	0.0009066	-9.34E-05	-0.000173	-0.0001134	-0.0001734	-9.34E-05	0.000147	0.0006166	0.000247
vitamin-c(g)	0.001088418	0.015	0.0010734	-0.005292658	-0.005292658	0.015707342	-0.004293	-0.005292658	-0.002292658	-0.00529	-0.003293	0.021707342	-0.00529
vitamin-b12(g)	1.05E-07	0.0009	0.0007947	7.88E-05	7.88E-05	7.88E-05	7.88E-05	8.18E-05	7.88E-05	7.89E-05	8.08E-05	8.08E-05	7.88E-05
vitamin-a(g)	2.18E-07	0.0006	0.0003818	2.69E-05	2.89E-05	2.59E-05	2.59E-05	2.60E-05	3.09E-05	6.39E-05	6.39E-05	6.39E-05	2.59E-05
calcium(g)	0.000189324	0.5	0.0003107	-37.59996893	-37.59996893	-37.59996893	-37.59997	-37.59996893	42.40003107	41.40003	37.40003	33.40003107	33.40003
vitamin-pp(g)	0.000175534	0.006	0.0001695	0.000783953	-0.000106047	0.000583953	-0.001196	-0.001086047	-0.001296047	-0.00112	-0.000336	0.004053953	-0.00012
vitamin-b6(g)	1.76E-05	0.0005	1.71E-05	-6.73E-05	-8.73E-05	0.00023271	-5.73E-05	-8.73E-05	1.27E-05	-8.73E-05	-5.73E-05	0.00028271	-6.73E-05

Figure 5.1: Validation of Results

5.4 Addressing Research Questions

The following table has shown which research question is met by which module in methadology.

Research objective	Corresponding module
Finding the dataset most suitable for Recommender system.	Dataset
Image recognition to recognize the food in plate.	Image Recognition module
Image segmentation to get the quantity of food.	Image Segmentation module
Saving the nutrient values in food log	Database module
Count of nutrient value to get the daily nutrient intake of the user.	Recommendation module
To recommend food based on the deficiencies of the child.	Recommendation module

Table 5.1: Research Objectives and Corresponding Methodology Modules

CHAPTER 6

Chapter 6: Conclusion

This project's meal recommender system is intended to help working women by making sure their kids eat healthily while attending daycare. The system offers a smooth and effective way to monitor diet by automating the processes of food identification, mass calculation, and nutritional analysis. The system precisely logs dietary intake and detects deficiencies by utilizing computer vision and an extensive food database. The recommendation module then makes dietary recommendations to make up for these deficiencies and improve children's health.

Although the system's current scope is restricted to fruits, future developments may include a greater range of food categories, which would increase its applicability and utility. Furthermore, by integrating user preferences into the recommendation process, the system could be further customized to meet the needs of each user, increasing its effectiveness and engagement.

6.1 Future Work

There are a number of directions that future research could take to improve the functionality and impact of the current system, even though it shows a lot of promise.

6.1.1 Expanding Food Categories:

The present framework only considers fruits. To make the system more complete, the database could be expanded to include more food categories like grains, vegetables, dairy, and proteins. The expansion would entail updating the image recognition and segmentation modules to handle a wider variety of food items, as well as curating a larger dataset.

6.1.2 Incorporating User Preferences:

By adding a feature that lets users enter their dietary restrictions and preferences, the recommendations may become more tailored to each individual. By taking these preferences into account, the system can make food recommendations that are not only satisfying to the user and more likely to be followed, but also in line with the child's dietary needs and tastes.

6.1.3 Enhanced Nutritional Analysis:

More advanced nutritional analysis tools that take into account macronutrients, fiber content, glycemic index, and other dietary factors in addition to micronutrients may be added to the system in future iterations. This would offer a more comprehensive picture of the diet and general health of the child.

6.1.4 Real-time Feedback and Alerts:

By putting in place real-time feedback systems and alerts, parents and other caregivers may be able to get quick information about their child's nutritional condition. To balance the diet for the day, the system might recommend additional foods or meals if a meal is deficient in a certain nutrient.

6.1.5 Mobile Application Integration:

Creating a mobile application could improve the system's usability and accessibility. A mobile app would be a useful tool for time-pressed caregivers because it would make it simple for parents to upload pictures of food, view nutritional logs, and get recommendations while on the go.

6.1.6 Machine Learning Enhancements:

Using cutting-edge machine learning methods could increase the precision of food segmentation and identification. The system's robustness and reliability would increase if models were trained on larger and more diverse datasets, which would improve the system's ability to handle a wider variety of foods and serving sizes.

6.1.7 User Interface Improvements:

Improving the user interface to make it easier to use and more intuitive might increase user satisfaction and engagement. User-friendly features like progress tracking, visual dashboards, and simple menus would increase system appeal.

In conclusion, there are many ways to improve the meal recommender system, even though it offers a useful tool for tracking and enhancing kids' nutrition in its current state. Through broadening its range, integrating user preferences, and utilizing cutting-edge technologies, the system has the potential to develop into an all-inclusive nutritional management instrument that fosters improved health outcomes for kids in childcare environments.

CHAPTER 7

Chapter 7: Recommendations

This chapter presents the recommendation of the proposed work.

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Appendix A

Achievements

If the thesis resulted to produce any publications or any product. This can be listed here.

APPENDIX B

Appendix A

The separate numbering of appendices is also supported by LaTeX. The *appendix* macro can be used to indicate that following chapters are to be numbered as appendices. Only use the *appendix* macro once for all appendices.

Annex ’A’

office order: 0986/29/ACB/SEECS

Date August 30, 2024

Th.ECL (MS Thesis Evaluation Check List)

Student Name:

Registration:

Cover and title page of the thesis

T1. Student’s name and registration number is written.

T2. Supervisor’s name is mentioned.

T3. Title of the degree is written correctly.

T4. University and school’s name are written correctly.

T5. Date of completion/defense (only year and month) is mentioned.

Style and formatting issues

S1. Consistent font (Times New Roman) is used throughout the thesis.

S2. Page numbering is done appropriately.

S3. Figures are readable and are aligned correctly.

S4. Captions for tables and figures use consistent format and style.

S5. Table of Contents/Figures/Tables follow proper indentation/styling.

S6. Chapter name and numbering follows consistent style.

References/Bibliography

R1. References are sorted on last name of authors (or in the order of citation in the text).

R2. References follow consistent style such as ACM or IEEE-Tran.

R3. Mandatory slots of references are filled correctly (such as Author, Title, Journal, Year).

General Issues

G1. Certificate of Originality signed by the student is present.

G2. Plagiarism report (from Euphorus) signed by supervisor is presented along with the thesis.

G3. Thesis is submitted within allowed time span for completion of thesis.

Abstract (Note: This section covers only the abstract of the thesis)

A1. There are no typing or grammatic mistakes in the abstract.

A2. Problem statement is clearly mentioned.

A3. Background to problem statement is also explained.

A4. Startling statement (preferably a paragraph) about the thesis/hypothesis is present.

A5. Implication of the startling statement is demonstrated briefly.

Results, Evaluation, and Conclusion

E1. Research is validated either empirically or analytically (Note: This doesn't cover quality of the results).

E2. Outcome of this thesis is contrasted with other similar research initiatives.

E3. Significance of this research is discussed in appropriate length.

Thesis Format

Sno	**HQ NUST Format**
1	Title Page
2	Thesis Acceptance Certificate
3	Approval Page
4	Dedicatoin
5	Certificate of Originality
6	Acknowledgement
7	Table of Contents
8	List of Abbreviation
9	List of Tables
10	List of Figures
11	Abstract
12	Main Body

Checklist for Components in Main Body

Sno	HQ NUST Fromat
1	Introduction
2	Literature Review
3	Methodology
4	Results
5	Discussion
6	Conclusion
7	Recommandation
8	Reference
9	Appendices
10	Index (Optional)

Additional Remarks:

OiC MS Thesis:

Date:

APPENDIX B: APPENDIX A

Office Order: 0986/29/ACB/SEECS

Date August 30, 2024

Th.ECL (MS Thesis Evaluation Check List)

Student Name:		
Registration:		
Cover and title page of the thesis		
T1.	Student’s name and registration number is written.	
T2.	Supervisor’s name is mentioned.	
T3.	Title of the degree is written correctly.	
T4.	University and school’s name are written correctly.	
T5.	Date of completion/defense (only year and month) is mentioned.	
Style and formatting issues		
S1.	Consistent font (Times New Roman) is used throughout the thesis.	
S2.	Page numbering is done appropriately.	
S3.	Figures are readable and are aligned correctly.	
S4.	Captions for tables and figures use consistent format and style.	
S5.	Table of Contents/Figures/Tables follow proper indentation/styling.	
S6.	Chapter name and numbering follows consistent style.	
References/Bibliography		
R1.	References are sorted on last name of authors (or in the order of citation in the text).	
R2.	References follow consistent style such as ACM or IEEE-Tran.	
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G1.	Certificate of Originality signed by the student is present.	
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E1.	Research is validated either empirically or analytically (Note: This doesn’t cover quality of the results).	
E2.	Outcome of this thesis is contrasted with other similar research initiatives.	
E3.	Significance of this research is discussed in appropriate length.	